AD-A097 622 DAYTON UNIV OHIO F/G 9/2

COMPUTER SIMULATION OF HUMAN PERFORMANCE IN ELECTRONIC PROCESSE--ETC(U)

JAN 81 A I SIEGEL, R F BACHERT F33615-77-C-0520

UNCLASSIFIED AFAMRL-TR-79-117 NL

1 OF 2

AD A
097622

AMRL-TR-79-117 LEVEL II

(12)

Dayton Univ., OH
105 350

COMPUTER SIMULATION OF HUMAN PERFORMANCE IN ELECTRONIC PROCESSED IMAGERY SYSTEMS

ARTHUR I. SIEGEL
APPLIED PSYCHOLOGICAL SERVICES, INC.
SCIENCE CENTER
WAYNE, PENNSYLVANIA

ROBERT F. BACHERT
AIR FORCE AEROSPACE MEDICAL RESEARCH LABORATORY

JANUARY 1981

Approved for public release; distribution unlimited.

AIR FORCE AEROSPACE MEDICAL RESEARCH LABORATORY
AEROSPACE MEDICAL DIVISION
AIR FORCE SYSTEMS COMMAND
WRIGHT-PATTERSON AIR FORCE BASE, OHIO 45433

NOTICES

TECHNICAL REVIEW AND APPROVAL

AMRL-TR-117

This report has been reviewed by the Office of Public Affairs (PA) and is releasable to the National Technical Information Service (NTIS). At NTIS, it will be available to the general public, including foreign nations.

This technical report has been reviewed and is approved for publication.

FOR THE COMMANDER

CHARLES BATES, JR.
Chief
Human Engineering Division
Air Force Aerospace Medical Research Laboratory

AIR FORCE/56780/5 March 1981 — 130

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE

READ INSTRUCTIONS BEFORE COMPLETING FORM

1. REPORT NUMBER: AMRL-TR-79-117	2. GOVT ACCESSION NO.: AD-A094 622
3. RECIPIENT'S CATALOG NUMBER	
4. TITLE (and Subtitle): COMPUTER SIMULATION OF HUMAN PERFORMANCE IN ELECTRONIC PROCESSED IMAGERY SYSTEMS	5. TYPE OF REPORT & PERIOD COVERED: Final Report
	6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s): ARTHUR I. SIEGEL, ROBERT F. BACHERT*	8. CONTRACT OR GRANT NUMBER(s): F33615-77-C-0520
9. PERFORMING ORGANIZATION NAME AND ADDRESS: Applied Psychological Services, Inc., Science Center, Wayne, Pennsylvania	10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS: 62202F; 7184-12-10
11. CONTROLLING OFFICE NAME AND ADDRESS: Air Force Aerospace Medical Research Laboratory, Aerospace Medical Division, AFSC, Wright-Patterson Air Force Base, Ohio 45433	12. REPORT DATE: January 1981
	13. NUMBER OF PAGES: 125
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office)	15. SECURITY CLASS. (of this report): Unclassified
	15a. DECLASSIFICATION DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

*Technology Development Branch
Human Engineering Division
Air Force Aerospace Medical Research Laboratory

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

Computers; Modeling; Simulation; Human Performance; Imagery Systems; Man-Machine Systems; Target Detection; Target Classification; Decision Theory; Problem Solving Theory; Communication; Human Operator

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

The psychological, analytic, and programmatic aspects for an integrated set of computer simulation subroutines are presented. The algorithms and modules were designed to add the realism of a human element to a MAIN network systems simulation model of the AN/UPD-X systems exploitation process. This process involves a multi-operator, multi-stage exploitation of targeting information gathered by an airborne side-looking reconnaissance aircraft. The design of

(Continued)

405350

Block 20 (continued):

generic modules was a primary goal. The theoretical basis in the behavioral sciences is presented, cast into quantitative terms, and formulated as programming specifications.

PREFACE

This study was initiated by the Human Engineering Division, Air Force Aerospace Medical Research Laboratory, Wright-Patterson Air Force Base, Ohio, 45433. The research was conducted by Applied Psychological Services, Inc., Science Center, Wayne, Pennsylvania, 19087. The work was performed in support of Project 7184, "Man-Machine Integration Technology," Task 718412.

The research sponsored by this contract was performed between August 1977 and November 1978 under Air Force contract F33615-77-C-0520.

We are indebted to others for their encouragement and assistance in the pursuit of this work. At the AMRL, Dr. Donald Topmiller provided considerable guidance and made a wide variety of useful suggestions relative to approach and contents. Mr. Lee Griffin provided information important to our understanding of the AN/UPD-X system's use and application.

At Applied Psychological Services, Stanley Tayler assisted in the definition of visual variables. Walter Lapinsky defined some of the user interface programming specifications, Eugene Welsand contributed to the definition of the first classification subroutine, and Larry Musetti assisted in the selection and definition of basic concepts to be incorporated in the decision subroutine.

TABLE OF CONTENTS

TABLE OF CONTENTS (Cont.)

TABLE OF CONTENTS (Cont.)

LIST OF ILLUSTRATIONS

LIST OF EXHIBITS

LIST OF TABLES

SECTION I
INTRODUCTION AND SUMMARY

This report presents the "operator performance" design requirements and definition of five different yet related models and algorithms for computer simulation subroutines or modules. Each of these was conceived and developed to operate interactively with a global simulation program whose goal is to simulate the principle ground-based man-machine operations involved in the AN/UPD-X system in which video type displays present processed data sensed by a side looking radar, mounted in a USAF reconnaissance aircraft.

Features of these algorithms were derived in each case from: (1) current human performance data and theory, (2) adaption of prior computer simulation models whose goals were similar to the current ones, or (3) a combination of these. The algorithms were designed for simulating four operator-dependent fuctions:
- (1) video scanning and target detection
- (2) target classification
- (3) decision making
- (4) interoperator communications.

In addition to some specific error condition indicators, each algorithm was specified to provide:
- (1) the simulated performance time of the operator(s)
- (2) an indication of the success or failure of the operator(s) action(s) or decision(s).

Design features or goals for the algorithms are:

(1) Generic. Generality was a primary goal. This is desired as a cost effective approach when various system design configurations are to be analyzed (as explained in the background section, this was the existing situation) and a procedures analysis* is to be performed. If the functional level is such that it can be found in numerous other applications then the writing of general routines is a sound approach. There is good reason to justify the allocation of the above given man-dependent functions to other applications, e.g., in a broad sense the scan and detect functions are applicable to many other visual target selection applications. The levels of functions are allocated to permit reassignment or trade-off between operators or groups of operators.

(2) Modularity. This design principle was adapted to facilitate future change or modification of models or submodels, hence adding flexibility and cost effectiveness. By proper grouping of functions, modules can be designed as independent, thus allowing independent development, verification, and maintenance and/or modification. An ideal goal for design and simulation is the development of a library of generic modules which can be utilized as building blocks in a properly structured top-down design. This approach is being recognized in industry as the most cost effective and utilized to eliminate redundancy and errors. To date, generic human performance models for simulation have been scarce.

(3) Optimum Interfacing. The algorithms are rich in variables, yet an attempt has been made in the design process to reduce complexity. Since these algorithms were defined without a complete description of total system simulation program available, it is anticiptated that some modification of the flow logic for the coded subroutines may be required during the programming and integration phase. Interactions between routines must, by design, be handled by the main simulation program as these are application dependent. In certain applications these interactions may be considerable, e.g., in a multi-operator task there can be considerable switching back and forth between scanning, decision, and communications. It was beyond the scope of this initial design stage to anticipate all the main program interfacing ramifications. Possible interactions between all elements is shown in a general way in Figure 1-1.

* analysis of operating procedures based on operator decisions and specific tasks; information-action requirements; task allocations; man-machine and intra-crew interactions; work-load criteria and mission scenarios.

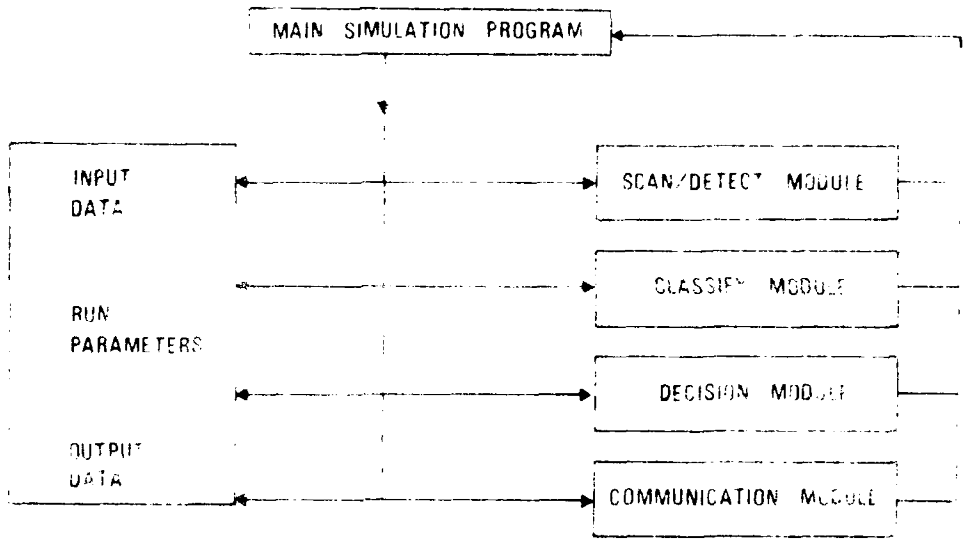


Figure 1-1. Global Model Interface to Human Oriented Modules

4) Verification and Validation. By using a modular design approach, verification is simplified. Both verification and validation should be a continuing process and certainly part of the next implementation phase.

5) Portability. All algorithms are to be programmed in Fortran. An objective of the programming phase will be to investigate requirements for interfacing with simulation programs such as SAINT (DUKET, WORTMAN et al.) and HOS (ANALYTICS), and while attempting to satisfy these still maintain generality and portability.

As indicated above these goals are not independent of each other; accordingly, when pursuing any one, care must be taken to estimate impact on the others.

The algorithms defined in this report model the following basic tasks or functions:

1. For the SCAN/DETECT algorithm
   — scanning a cathode ray tube (CRT) screen for the presence of targets
   — detecting such targets
2. For the CLASSIFY algorithm
   — [illegible] target [illegible]
3. For the CLASSIFY algorithm
   — [illegible] type of target [illegible]

- For the DECISION algorithm:
  - [illegible] among [illegible] mission [illegible] [illegible] [illegible] [illegible] accomplishment [illegible] assigned mission tasks. This constitutes [illegible] selection of one from [illegible] number of alternatives.
- For the COMMUNICATION algorithm:
  -- modeling of oral interpretor communications during mission operations.

In addition, each of these five algorithms determines the amount of operator time required in the simulated performance of these tasks and determines whether or not the simulated operator(s) performed these tasks adequately, i.e., successfully or unsuccessfully.

Sections II through V of this report contain descriptions of the individual simulation modules. In each case, the pertinent behavioral theories are examined and summarized. These are organized into selected human oriented techniques which represent the logical bases for the simulation. At the end of each chapter, a programming oriented description of the module is presented. Here the specific input data items from and returned to MAIN are itemized and explained. A summary flow chart of the logic of each module is presented. A second block diagram with adequate detail on numerical methods, sequencing, and interaction is also provided so as to define the computer program modules which may be prepared from these designs.

SECTION II
BACKGROUND

The AN/UPD-X system output is a group of near real-time reconnaissance reports on tactical targets under all weather conditions. Data are collected via radar aboard an aircraft and transmitted to the ground via a data link. The information is then digitized, processed, and passed to the Exploitation subsystem. The Exploitation subsystem mission requirements include target detection, classification, location, and trend analysis. The objective of the global simulation program, which the results of this report were to support, was to concentrate its efforts on this subsystem.

The AN/UPD-X system was in the design or "evaluation of alernatives" phase during the model development period. As a result, the human oriented subroutines were developed in a sufficiently general way to allow their use during comparative simulation of alternative AN/UPD-X system designs—even those developed by different industrial contractor teams including different AN/UPD-X equipment configurations and diverse operator sequences. One of the goals of the total model is, then, the simulation of alternative system designs to allow the USAF to evaluate the comparative "value" of the alternatives. Another element which was established as a requirement or assumption was the potential for simulating multiple operators performing the monitoring, communications, and decision-making functions.

Function allocation and procedures analysis would be the resulting products of the simulation studies.

81 4 10 022

SECTION III
SCAN/DETECT MODULE

OVERVIEW OF SCAN AND DETECTION

Consider an AN UPD-X video terminal, monitored by an operator, displaying a replica, (i.e., a two dimensional view) of a geographical area of the earth's surface and an operator scanning this CRT to detect targets.

This section describes the development of a subroutine to simulate such an operator moving his eyes from one fixation point to another over the screen to accomplish the scan and then, having scanned to a point at which one or more targets is located "nearby" to simulate the detection of the target or targets by the operator. Six different modes of scanning the screen are provided in the simulation:

Scan Mode	*How Points are Selected*
random	at random
sequential	left to right at fixed increments
area of emphasis	4 points in designated rectangular area, 2 at random and repeat
corners and center	10 points in corner and center areas, 5 at random, and repeat
directed	as designated by the MAIN program
other	to be defined

Although the view is presented on a cathode ray tube, it is assumed here that the surface is flat and the scene presented is rectangular.

An overview of this subroutine is shown in Figure 3-1. Figure 3-1 also indicates that each time the subroutine is entered, the subroutine:

(1) identifies all first-time presented targets as either cued or not cued (cueing includes flashing, moving symbols, color contrast or the like)
(2) determines one or more successive fixation points to represent the scan
(3) determines probabilistically whether or not one or more targets are detected at each fixation point
(4) terminates the selection of fixation points when the first detection is successful
(5) calculates the total operator scan-detect performance time.

Accordingly, the module's purposes are:
(1) to determine the coordinate position of successive fixation points until a valid target is found within a prespecified distance of a fixation point
(2) to determine the elapsed AN/UPD-X operator time to make the scan(s) and the detection
(3) to determine correctness of the detection.

FACTORS AFFECTING TARGET DETECTION

Detection is the most elementary response of the visual system and is the response which must precede any other action response to the target. For detection in a two dimensional, monochromatic viewing situation, a difference in the luminous intensity of one portion of the visual field relative to other portions is the fundamental cue. The likelihood with which such a difference in luminance will be detected by an intact observer is dependent in part on: (1) the position of the target relative to the observer's line of sight, and (2) a variety of measurable stimulus (target) attributes.

Target shape is one of the target attributes considered by the detect subroutine. Specifically, the border between the target and the background, if traced, will form a figure. The figure may be regular or irregular. It may be closed or open.

Characteristics of a target's border or contour may vary. At the border of a target which is "sharp," the change from target luminance to background luminance is quite abrupt [as shown in Figure 3-2(a)]. A

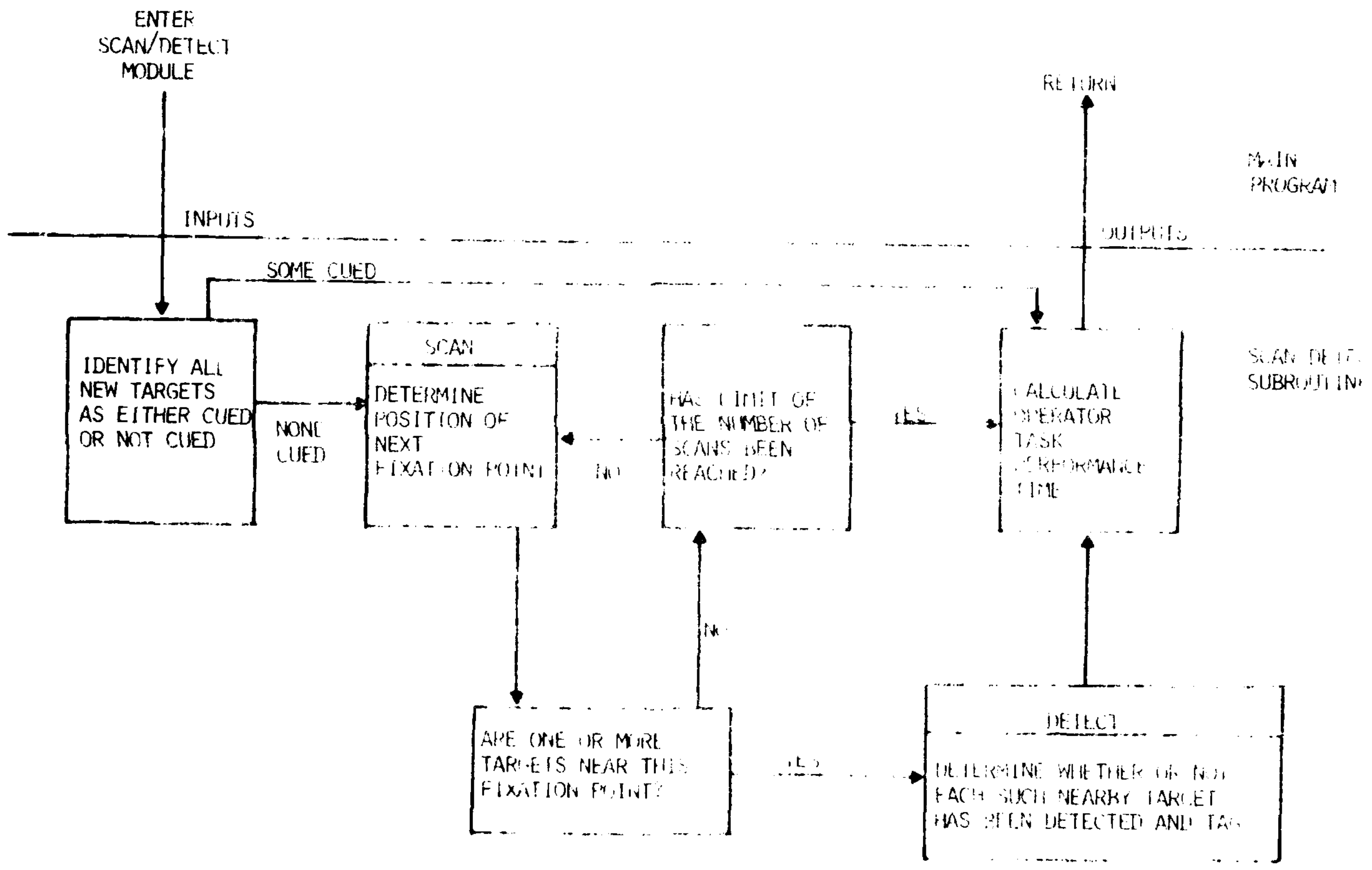


Figure 4-1. Scan/Detect Subroutine and Its Interface to the Main Program

"blurry" target exists when the change between luminance levels at the target's border is relatively gradual (as shown in Figure 3-2(b)).

Target images may be artificially processed to increase the contrast at the borders. The luminance changes at a border so processed are shown in Figure 3-2(c). This type of processing enhances the prominence of a border above that of a border of the type shown in Figure 3-2(a).

Finally, the characteristics of a target may be constant or variable as a function of time: a target may flash or it may move. Such cues increase target detectability, and should be considered in the model since this capability is expected to be a requirement in the AN/UPD-X system.

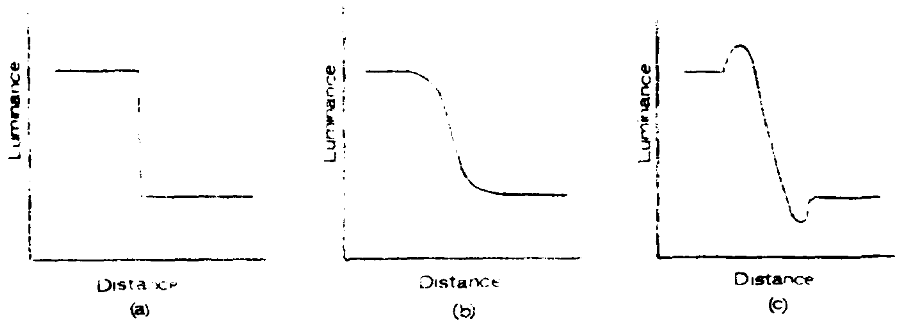


Figure 3-2 Change of luminance at a "sharp" border of a visual target (a), at a "blurred" border (b), and at an artifically enhanced border (c).

Target size is another target attribute consideration. Size is defined by the visual angle that the target subtends at the eye of the observer.

The detection module, described here, allows variation in each of the attributes to influence detection probability.

OTHER VARIABLES

Within the module, other variables affect the probability of target detection by adjustment of target parameters to assume the characteristics of an equally prominent circular fixated target. The probability of detection of this equivalent target is computed, and this probability value is taken as the probability of detection of the original target.

As an example, if a target x degrees from the visual axis must be twice as large to be detected as a comparable target at the fixation point, then the probability of detection equation is applied to an equivalent target which is one-half the size of the actual off-axis target. Similarly, if a target of a given shape must possess twice the area of a circular target to be detected, then the probability of detection equation is applied to an equivalent circular target which is one half the area of the actual target.

SCAN/DETECT MODULE DESCRIPTION

A somewhat more detailed presentation of the logic flow of the scan/detect module is presented in Figure 3-3. The succeeding paragraphs describe the background information, computational logic, equations and other data relevant to stochastic digital simulation of visual detection. The programming aspects are presented at the end of the chapter.

TARGET CUEING

Before entering the principal detection logic, a test is made to determine whether or not a cued target exists over the entire display.

In a processed target situation (such as the AN/UPD-X), target conspicuity may be artifically increased by accentuating features external to the raw video return. Suitable cueing, through the use of fixed, flashing, or moving symbols of high brightness or color contrast, may cause detection of a cued target to be essentially certain with minimal latency. All cued targets are assigned a probability of detection of 1.00-RD (where RD is a random deviate) and cued targets will be the first targets to be fixated for classification by the observer.

Accordingly, in block 1 of Figure 3-3, the presence of unprocessed cued targets is tested. If cued targets exist, they are identified and selected for subsequent classification, processing continues at block 1 of Figure 3-3.

UNCUED TARGETS

Processing for probability of detection of uncued targets is applied only to targets within about 12 degrees of the present fixation point. The present fixation point of the observer is known to the scan/detect subroutine.

The angle, α, between the fovea and each target is computed based on the x and y coordinates of the point of fixation (from the scan calculation), the coordinates of the center of each target which are supplied as input, and the eye-to-screen viewing distance (also supplied as input but modified by a random deviate.) The off-axis angle, α, is retained with each target for later use.

The ability of the eye to detect stimuli which are more than 12 degrees from the fovea appears poor, as will be described subsequently. In addition, data are not available which describe detection of targets over 12 degrees from the fovea, as a function of the variables addressed here.

At block 2 of Figure 3-3, all targets within 12 degrees of the point of fixation are identified along with their characteristics. The target characteristic input values which are associated with each target are:

C — target to background contrast
LWR — target length to width ratio
TA — target area (square minutes of angle)

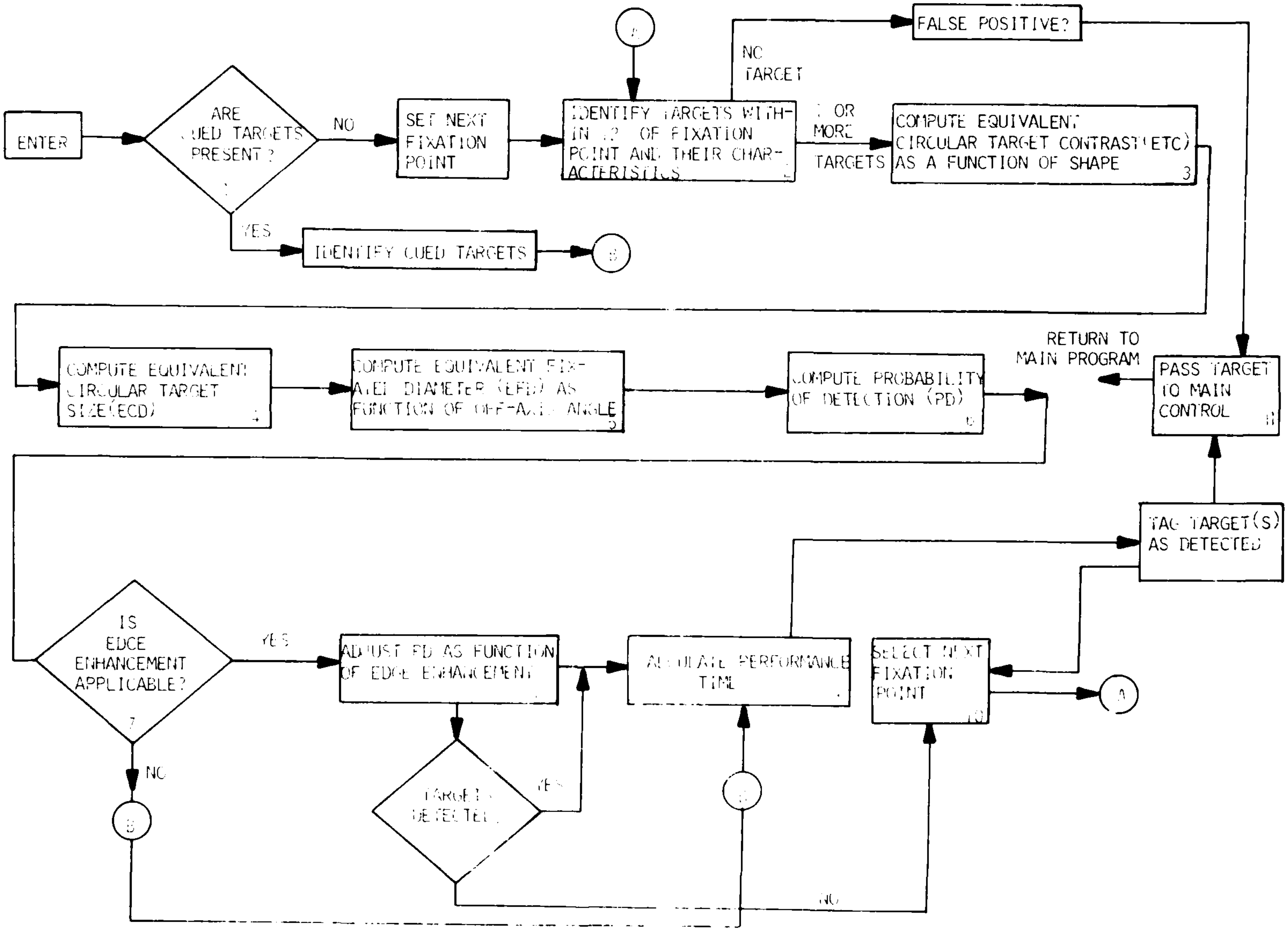
In each succeeding block of Figure 3-3, the computations are applied to each identified target sequentially.

TARGET SHAPE

The detectability of targets is affected by their shape. The effect of shape is accounted for by the computations of block 3, Figure 3-3.

Lamar, Hecht, Shlaer, and Hendley (1947) studied the relationship between target length to width ratio and contrast required for detection. They employed rectangular targets of various areas. Their data were based on experimental trials in which the background luminance was 17.5 foot lamberts. This level is in the moderate photopic range, as are other data applied in the present simulation module. Relative detection thresholds for the targets of Lamar et al. are presented in TAble 3-1. Each row of Table 3-1 shows ratios of detection threshold of other targets to that of the detection threshold for the target of the same area having a length to width ratio of 2:1. Examination of the rows of Table 3-1 shows that as the length to width ratio of a target increases, with target area held constant, the contrast required for detection increases substantially. Examination of the columns of Table 3-1 indicate that the increase in required contrast is largely independent of target area over a substantial range.

The mean relative threshold at each level of target eccentricity is shown towards the bottom of Table 3-1. These mean values are approximated by the following equation within the model:


ENTER
ARE CUED TARGETS PRESENT?
NO
YES
SET NEXT FIXATION POINT
IDENTIFY CUED TARGETS
IDENTIFY TARGETS WITHIN OF FIXATION POINT AND THEIR CHARACTERISTICS
NO TARGET
FALSE POSITIVE?
1 OR MORE TARGETS
COMPUTE EQUIVALENT CIRCULAR TARGET CONTRAST (ETC) AS A FUNCTION OF SHAPE
3
COMPUTE EQUIVALENT CIRCULAR TARGET SIZE (ECD)
4
COMPUTE EQUIVALENT FIXATED DIAMETER (EFD) AS FUNCTION OF OFF-AXIS ANGLE
5
COMPUTE PROBABILITY OF DETECTION (PD)
RETURN TO MAIN PROGRAM
PASS TARGET TO MAIN CONTROL
TAG TARGET(S) AS DETECTED
IS EDGE ENHANCEMENT APPLICABLE?
7
YES
NO
ADJUST PD AS FUNCTION OF EDGE ENHANCEMENT
TARGET DETECTED
YES
NO
PERFORMANCE TIME
SELECT NEXT FIXATION POINT
A
B

FIGURE

RT = .7183(LWR)^.3077

in which:

RT = relative threshold
LWR = length to width ratio

Relative threshold values predicted by this equation are presented in the last row of Table 2-1. The results of this calculation are then used, along with a random deviate, to calculate an equivalent circular target contrast, ETC, for targets as a function of length to width ratio. In the simulation, a lower bound of [illegible] is applied to the computed relative threshold value. The contrast of targets having a length to width ratio of 2:1 or more is divided by the predicted relative threshold for targets of the appropriate degree of eccentricity.

TABLE 3-[illegible]

RELATIVE DETECTION THRESHOLD CONTRAST FOR TARGETS OF VARIOUS LENGTH TO WIDTH RATIOS AND AREAS RELATIVE TO DETECTION THRESHOLD OF A TARGET WITH LENGTH TO WIDTH RATIO OF 2:[illegible]
(Based on data of Lamar et al., [illegible])

Target Area in Square Minutes of Visual Angle	Length to Width Ratio 2:1	7:[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	1.00	1.19	1.4[illegible]	2.1[illegible]	1.0[illegible]
[illegible]	1.0[illegible]	1.28	1.[illegible]	2.7[illegible]	4.4[illegible]
[illegible]	[illegible]	1.16	1.4[illegible]	2.[illegible]	[illegible]
[illegible]	1.0[illegible]	1.17	[illegible]	2.4[illegible]	[illegible].47
[illegible]	1.0[illegible]	1.2[illegible]	[illegible]	2.7[illegible]	[illegible]
[illegible]	1.00	1.2[illegible]	[illegible].94	2.7[illegible]	[illegible]
Mean	1.00	1.2[illegible]	1.6[illegible]	2.5[illegible]	[illegible]
Prediction by model's approximation formula	0.89	1.3[illegible]	1.8[illegible]	2.65	[illegible]

Glimpse duration during visual search has been generally reported to be approximately [illegible] second (W[illegible] 197[illegible]; Williams, Fairchild, Graf, Juola, & Trumm, 1970). Accordingly, the data of Taylor are [illegible] to calculate an equivalent fixated target size as a function of off-axis angle.

Taylor's curve may be closely approximated by the logarithmic equation:

Relative acuity = .8525 - .24ln$a$

where

a = angle of the target from the fovea in degrees

That is:

ETC = C/RT

in which

ETC = equivalent circular target contrast
C = actual contrast ratio
RT = relative threshold

This [illegible] yields the contrast of a circular target of equal area which is assumed [illegible] take [illegible] target.

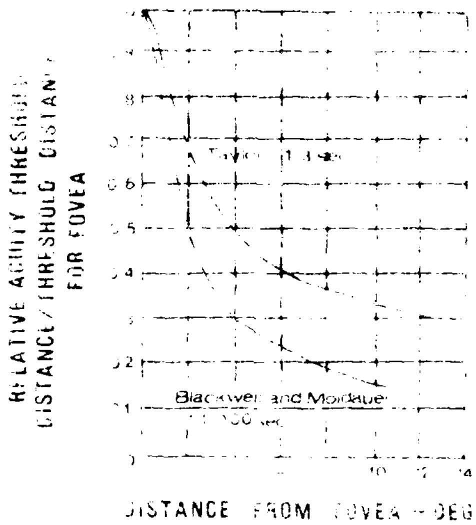


Figure 3-4. Relative acuity as a function of distance from fovea [data are for circular targets and background luminance of 0.75 ft-L, data reported from Taylor (1961) and Blackwell and Moldauer (1958), after Ozkaptan et al., (1968)].

[illegible] the contrast value has been [illegible] that [illegible] to determine circular target, the diameter of an equivalent circular target is determined next. To be consistent with the application of the data [illegible] we replace the target dimensions with those of a circular target of equal area. This is [illegible] block 4 of Figure 3-3. Given the area of a target, the diameter of a circular target of equivalent area [illegible]

$$ECD = 2\sqrt{TA/\pi}$$

[illegible] which

ECD = equivalent circular target diameter (minutes of arc)
TA = target area (square minutes)

PERIPHERAL EFFECTS

The size of an object which may be detected by an AN/UPD-X or other CRT observer varies as the image moves from the fovea, the area of the retina having greatest visual acuity, to peripheral areas of the retina. The model deals with this phenomenon in block 5 of Figure 3-3.

Wertheim demonstrated the relationship between acuity and angle from the visual axis in 1894 (Chapanis, 1949). Wertheim found acuity to drop rapidly over the first few degrees of displacement of a target from the fovea. He found, for example, that to be detected at a point 15 degrees from the fovea, a target must be approximately five times larger than a detectable target which is fixated. Ozkaptan et al. (1968) reported more recent work of Blackwell and Moldauer (1958) and of Taylor (1961). Blackwell and Moldauer studied relative acuity as a function of angluar distance from the fixation point for stimuli presented for [illegible] second, while Taylor's data were collected using stimuli which were presented for [illegible] seconds. Their results, as summarized by Ozkaptan et al. (1968), are presented in Figure 3-4.

The results of applying this formula are:

Off-Axis Angle	*Graph Value*	*Calculated Value*
0.9°	.90	.88
1.3°	.80	.79
1.9°	.70	.70
2.7°	.60	.61
3.8°	.50	.53
5.7°	.40	.43
12.1	.30	.25

In order to determine target size of an equally visible fixated target, the equivalent circular target size is multiplied by the relative acuity at that off-axis angle.

For example, consider an AN/UPD-X target image whose center is 3.8 degrees from the fovea. From the values presented above, the calculated relative acuity for targets displaced 3.8 degrees from the visual axis is .53. A target, then, is assumed to be equally detectable at the fovea if it is .53 as large as a target which is 3.8 degrees from the fovea. Thus, a target subtending 2.0 degrees which is 3.8 degrees from the fovea is assumed to be equally detectable as a target subtending 1.06 degrees which is at the point of visual fixation.

In the detection module, in accordance with this logic, equivalent target diameter for targets presented in the peripheral retina is replaced by equally visible fixated target diameter, computed as equivalent target diameter multiplied by relative acuity plus or minus a small random deviate. That is:

$$EFD = ECD(.8525 - 24 \ln \alpha) \pm (RD)$$

in which:

EFD = equivalent fixated target diameter (minutes of arc)
ECD = equivalent circular target diameter (minutes of arc)
α = angle of the target from the fovea (degrees)
RD = random deviate

It is likely that plots of relative acuity within various planes about the visual axis would not appear identical. Wertheim's original work showed dissimilar plots of relative acuity as a function of displacement into the nasal or temporal portions of the retina. However, the data employed in the adjustment for distances off-axis are thought to be representative. The technique is applied to all targets appearing off-axis regardless of direction.

The threshold luminance required for detection of a peripheral target is also elevated in comparison with a foveal target (Taylor, 1961; Kinzley & Akerman, 1976; Ward, 1977). However, it does not seem appropriate to further adjust visibility of peripheral targets for luminance, since it appears that the requirements for additional size and for additional luminance for detection of fixated targets may be consequences of a single phenomenon.

TARGET BRIGHTNESS/DETECTION

To this point in the logic, adjustments have been made in the simulated target to produce characteristics of a foveal equivalent target. The detection probability is calculated in block 6 of Figure 3-3. This computation is based on equivalent target contrast and other previously calculated equivalent foveal target characteristics.

Heinz and Lippay (1928) studied the probability of seeing circular targets of varying size as a function of brightness contrast with the background. Targets of six sizes were presented at the point of fixation. The visual angles subtended by the targets varied from 11 minutes to 183 minutes. These angular subtenses correspond to .05 inch to .85 inch diameter cathode ray tube targets viewed from 16 inches.

The data of the subject of Heinz and Lippay are presented in Figure 3-5. These curves were presented by Brown and Mueller (1965). The x and y axes have been converted to contrast ratio ($\Delta I/I$) and probability of detection, respective.

A straight line of approximation was fit in Figure 3-5 to the portion of each target size curve falling between the .20 and .80 probability values. Inspection of these lines indicates that those associated with the three small targets (the curves to the right) have very similar slopes. The lines approximating detection probability of larger targets appear to diminish in slope as target size increases. Each of these two groups of three lines may be described by a separate equation.

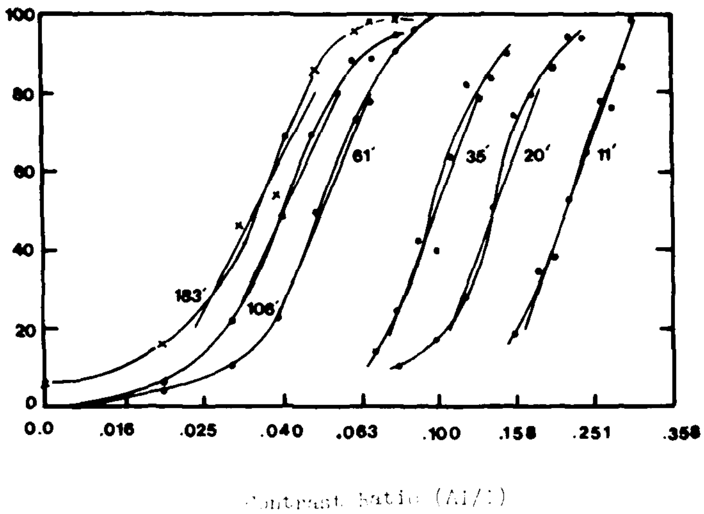


Figure 3-5. Probability of detection of foveally presented circular test targets of six diameters as a function of contrast ratio [data from Heinz and Lippay (1928), after Brown and Mueller (1965), rescaled].

In the case of the small targets, detection probability may be described as a function of equivalent target contrast and equivalent target diameter by the following equation:

$$PD = [2.79 (\log 100\ ETC) + 1.90\ EFD - 5.19]/100$$

in which:

EFD = equivalent fixated target diameter (minutes)
ETC = equivalent circular target contrast
PD = probability of detection

The equation presented above may be viewed as a linear equation of the form $y = mx + b$, in which the y intercept, b, may vary. The slope, m, in the equation equals 2.79. The applicable y intercept is computed as 1.90 EFD -5.79. This equation reproduces the data related to small targets shown in Figure 3-5 with considerable accuracy. Typical results are:

Target Size	[illegible]	Probability of Detection: Computed	Probability of Detection: Actual
11	[illegible]	[illegible]	[illegible]
[illegible]	.8	79	80
20	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	80	[illegible]

Data describing the probability of detection of the large targets of Heinz and Lappay may similarly be described as a function of the same variables by the equation:

$$PD = ((-.0358EFD+2.68)\log(\text{[illegible]}ETC)+.59\ln EFD-.61)/1.0\text{[illegible]}$$

This equation may also be viewed as a linear equation of the form y = mx+b, except that the slope may vary as a function of target size and the y intercept may also vary as a function of target size. Slope is computed as -.0358EFD+2.68, and the y intercept, b, is computed as .59lnEFD-.61. This equation fits the applicable data of Figure 4 with considerable accuracy, as shown below.

Target Size	[illegible]	Probability of Detection: Computed	Probability of Detection: Actual
[illegible]	[illegible]	21	[illegible]
61	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]

The slope of the line based on the large target equation does not equal the slope (2.79) of the small target equation until target size becomes a negative value. A point of transition from one equation to the other must therefore be selected on other grounds.

A retinal or central nervous system process seems to make detecting small targets different from detecting large targets. For small targets, perception seems to be governed by the product of luminance and size of a target, so that a small target of high contrast may be equally detectable to a somewhat larger target of correspondingly lower contrast. Pieron (1929) demonstrated retinal summation of targets of up to one degree diameter when presented to the fovea. Other workers have demonstrated strong summation effects for larger targets presented to the peripheral retina (Woodworth & Schlosberg, 1954). These data seem to indicate a difference in the way in which visual targets larger than one degree are processed as compared with the way smaller targets are processed. Accordingly, the model employs the small target equation to compute probability of detecting targets up to 60 minutes in size. The probability of detecting targets 61 minutes or more in size is calculated through application of the "large target" equation.

The formula for predicting detection of large targets does not hold at the extremes of target size and contrast. The computed probability of detecting relatively small targets of low contrast is negative. The predicted probability of detecting targets possessing relatively high contrast exceeds 1.0. For targets of over 200 minutes diameter, detection probability initially climbs with increasing contrast, then falls. These areas in which the large target equation is not applicable, are shown in Figure 3-6.

Within the simulation, the following limits are set:

- If $C < .0373e^{-.00382EFD}$ then PD = 0.0. Without this restriction, PD becomes negative with decreasing contrast.

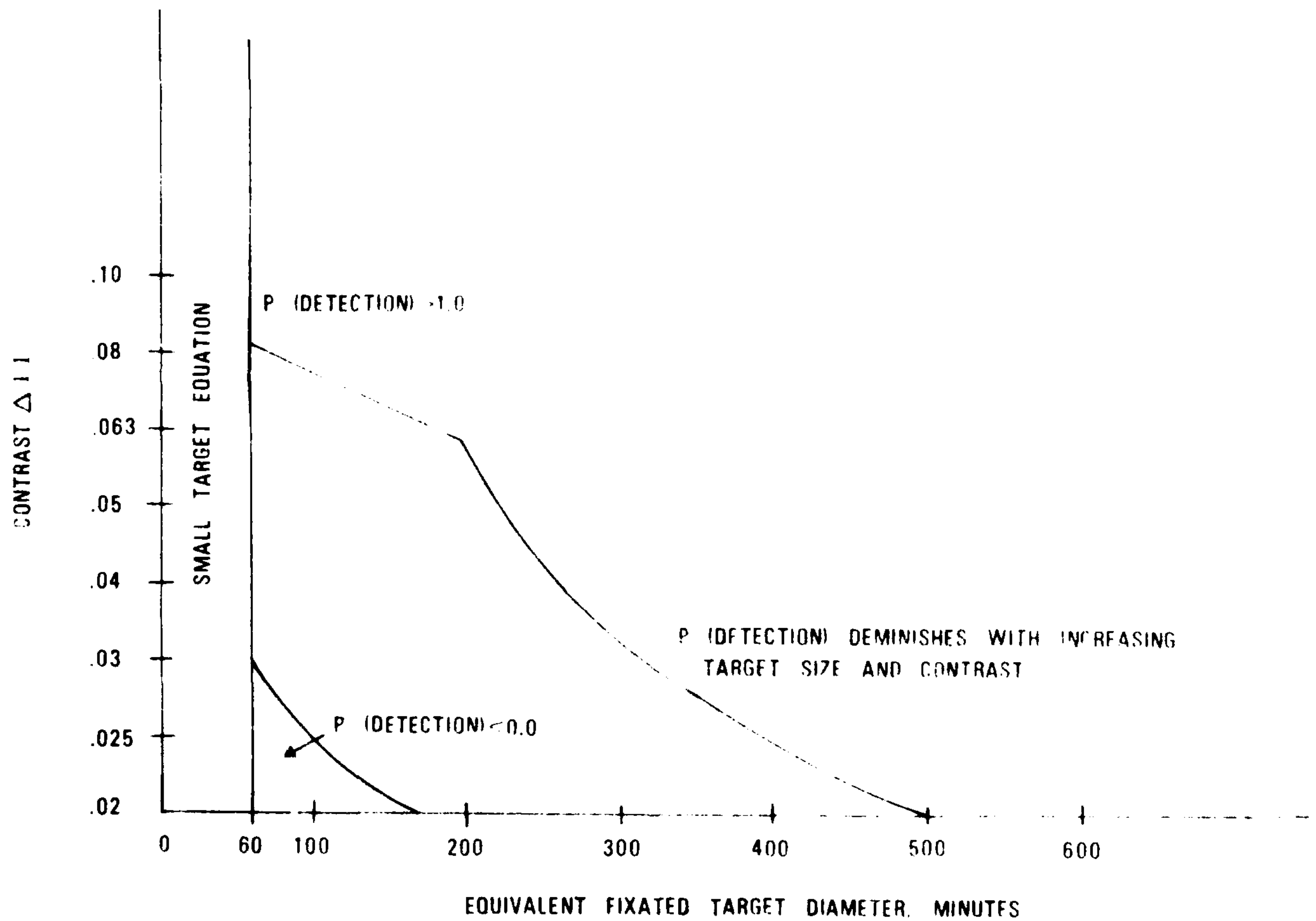


FIGURE 3-6. LIMITS TO APPLICABILITY OF PROBABILITY OF DETECTION EQUATION FOR LARGE TARGETS

- If $C > .0907e^{-.00317EFD}$, then set $C = .0907e^{-.00317EFD}$ and PD is computed normally. Without this restriction detection probability decreases with increasing contrast.

- If $C > -.000222EFD+.0944$, then PD = 1.0. Without this restriction, PD exceeds 1.00. (If this restriction and the previous restrictions are both violated, then PD = 1.00.)

POSITIVE VERSUS NEGATIVE CONTRAST

The detectability of targets presented on cathode ray tubes when targets possess higher luminance than the background (positive contrast) was compared to the detectability of targets of lower luminance than the background (negative contrast) by Harriman and Williams (1949) and by Baker and Earl (1968). Neither study found differences in detectability of targets due to algebraic sign of target contrast. Accordingly, we calculate the probability of seeing targets on the basis of the absolute value of target contrast.

IMAGE ENHANCEMENT

Brainard and Caum (1965) investigated the effect of an image enhancement process on performance of various detection and classification tasks which were applied to video processed aerial photographic imagery. To produce the imagery tested, air photos were deliberately defocused by contact printing through ground glass. The blurred prints were then displayed on a television monitor in unmodified form and with enhancement. The enhanced imagery was composed of this video signal and its negative second derivative. A higher level of gain (amplification) was also applied in processing the enhanced imagery. The primary subjective effect of the enhancement technique was to sharpen the blurred contours of the unprocessed imagery. A number of detection and classification tasks were studied, and a variety of performance measures were reported. The measure reported by Brainard and Caum which is most similar to detection as defined here involves proportion of targets detected. The proportion of targets detected on processed imagery was 60 percent greater than the proportion of targets detected on unprocessed imagery.

In the current AN UDP-X model subroutine, the findings of Brainard and Caum are applied by multiplying the probability of detection of all targets by 1.6, if image enhancement is applicable. That is:

$$\text{Enhanced PD} = 1.6\,(\text{PD}) + \text{RD}$$

This computation is performed in block 8 of Figure 3-3, if edge enhancement is applicable, as determined in block 7.

SELECTION OF SUBSEQUENT FIXATION POINT

At this point in the processing, control returns to the scan portion of the subroutine to select the next fixation point if no targets were detected. If one or more targets was detected, then performance time is calculated.

PERFORMANCE TIME

It appears fairly standard that observers maintain fixation on a point for approximately .33 seconds. Values in this area were found by Williams, Fairchild, Grauf, Juola, and Trumm (1970) and by Ward (1977).

The data of Williams et al. (1970) indicated a mean fixation period of .444 sec. with a standard deviation of .209 sec. These values include time required for movement of the eye, detection, perception, and selection of the next fixation point. Further breakdown of the time taken for fixation is unnecessary in the present context. A stochastically determined fixation time, based on the parameters listed above, and the number of scan eye fixations is calculated in block 9 of Figure 3-3.

In calculating performance times, which include one or more eye fixations plus a detection operation, the concept of operator stress as previously developed by Siegel and Wolf (1969) is employed. Stress can be defined here as the state of mind of the AN UPD-X operator when responding to a dynamic situation in which targets have a limited viewing time. Current psychological theory suggests that increased stress (due possibly to greater number of potential targets in this application) acts as an organizing agent. Accordingly, this subroutine incorporates a stress function in which a no stress situation is the base condition and the mean conditions and data above apply. Stress buildup will result in decreased performance times until a condition is reached which represents a stress threshold. After this point, if stress continues to build up, the effect will be disorganizing and significantly higher performance time will result. Thus, the stress threshold corresponds to an operator's break point before which his performance is enhanced and beyond which his performance deteriorates.

COMPARISON WITH VARIABLES ADDRESSED IN OTHER MODELS

Greening (1976) reviewed in detail six "principal" models of air-to-ground visual target acquisition. The application of the present model differs from those reviewed by Greening. However, the range of variables addressed is comparable. The incorporation of variables applicable to the present model and to those reviewed by Greening in the various models is shown in Table 3-2. Variables applicable only to air to-ground models, such as color contrast or masking, and those applicable only to the present model, such as cueing and edge enhancement, are not addressed in Table 3-2. The numbers of variables incorporated in the various models are comparable.

TABLE 3-2

VARIABLES INCORPORATED IN PRESENT MODEL AND IN SIX AIR-TO-AIR MODELS REVIEWED BY GREENING (1976)

Variables	*Present Model*	*MARSAM II (Honeywell)*	*GRC A (General Research Corp.)*	*SRI (Stanford Research Institute)*	*VISTRAC (Sandia Corp.)*	*DETECT II & III (U.S. Air Force)*	*AUTONETICS (Autonetics, Rockwell)*
Scene Characteristics							
Target Size	✓	✓	✓	✓	✓	✓	✓
Target Shape	✓				✓		
Complex Targets		✓		✓	✓		
Target Contrast	✓	✓	✓	✓	✓	✓	✓
Clutter		✓	✓				
Areas of low Target Likelihood	✓	✓					
Observer Characteristics							
Foveal Threshold	✓	✓	✓	✓	✓	✓	✓
Peripheral Threshold	✓	✓	✓		✓	✓	
TOTAL	6	7	5	4	6	4	3

PROGRAMMATIC ASPECTS OF SCAN/DETECT SUBROUTINE

The human-effects aspects described above are now summarized and embedded into a computer subroutine to simulate an operator performing the scan and detection functions.

INPUTS

The data items shown in Table 3-3 are required as input to the scan-detect subroutine. It is assumed that these data will be available either as a result of input to the global simulation model as parameters (e.g., item 7, operator speed proficiency) or generated by the main program (e.g., item 16, data about each target).

The subroutine provides for any one of six modes of eye scan (item 1 of Table 3-3), as a function of the operator number, M. Thus, each operator is assumed to have a particular scan technique which can be modified by MAIN as a function of type of task, time since mission start, or other pertinent factor.

The random scan (mode R) generates X and Y coordinates (XCORD and YCORD) at random anywhere inside the display. For modes S, C, and E, the next fixation point depends on the coordinates of the preceding one. In modes C and E the module maintains a cycle counter for scan, IS (see Table 3-3, item 10). The sequential (S) mode finds successive fixation points moving horizontally in X with increment DELTAX until the border and then again from left to right a distance of DELTAY.

The corners and center mode (C) selects 10 random points in the corner and center areas sequentially, then five points anywhere, and so on. The area of emphasis mode (E) generates four fixation points in the designated primary area, followed by two at random, and so on. The directed mode (D) generates no fixation points but uses the one provided by the main routine. This provides for the case in which one operator has selected a target and passes it to another who is also to be simulated. For the scan subroutine, we introduce the following concepts:

1) the viewing area has coordinates as shown in Figure 3-7

2) the display is of a given size and fixation is limited to the display area as defined by its length and width (border)

3) all dimensions are in inches

4) the rectangle is divided into six areas, denoted SAREA, when the scan mode E (area of emphasis) is selected.

TABLE [illegible]

PARAMETERS AND INPUTS FOR SCAN DETECT MODULE

Parameter	*Data Name*
Scan mode indicator R — random S — sequential C — corners and center E — area of emphasis D — directed T — other, to be defined	SM[illegible]M
Scan border — a dimension indicating the size (inches) of a border around outer edge of the rectangular viewing area in which fixation points will not fall.	SBORDER
Increments DELTAX and DELTAY (inches) used in sequential scan to move to the next fixation point. Maximum value [illegible], Minimum value [illegible]	DELTAX DELTAY
Scan corner — a dimension indicating the size (inches) of corners in corner & centers mode scans $0 \leq$ SCORNER $\leq$ YMAX/[illegible] SCORNER $\geqq$ SBORDER	SCORNER
Scan area — an area code (from 1 to 6) indicating the primary area of emphasis for the scan if the scan mode is E (area of emphasis).	SAREA
The coordinates of the most recent fixation point	(XCOORD, YCOORD)
Operator speed proficiency nominal; $\leq$1 faster; $\geq$1 slower M operator number	F(M)
Current stress value of operator M. STR(M) $\geq$ 1. Related to the visible processing workload (backlog or no. of unprocessed targets)	STR(M)
Stress threshold value for operator M (value of stress at which performance changes for the worse)	STRM(M)
Scan number in the repeatable cycle for corners and area of emphasis mode *Scan Mode* — *Maximum Value of IS* C — 12 E — 6	IS
Radius of a circle within which the existence of one or more targets will terminate the scan processing. Recommended range is 2.76 to 4.04" corresponding to a 12° visual angle at the average distance of 13-19" from the operator's eye to fixation point	VDR
Maximum number of fixation points permitted to be selected in one call of the scan module (Default value 100.)	MAXPTS
Probability that any target will be cued	CUEP
Time required by the average operator under no stress to change fixation points and detect targets, if any.	AVGTM

TABLE 3-3 (CONT'D.)

15.	Standard deviation of average scan time. Recommended value: SIGMA = 0.209 secs.	SIGMA
16.	Data relating to all targets (IT=1,...,ITMAX) for a total simulation mission iteration.	
	a. Visibility indicator 0-not visible to operator now 1-visible to operator for 1st time 2-visible to operator, not 1st time	V(IT)
	b. Position coordinate of the most recent fixation point:	
	X-coordinate	TX(IT)
	Y-coordinate	TY(IT)
	c. Target luminance difference i.e., target to background contrast ratio.	C(IT)
	d. Target length-to-width ratio.	LWR(IT)
	e. Target area (square minutes of visual angle for a viewer whose eye is 16 inches from display.	TA(IT)
	f. Detection classification status 1-consider for detection 2-detected 3-classified 4-passed to another operator 5-active 6-failed to detect	DCS(IT)
	g. Target cue, status: 0-not yet determined (by subroutine) 1-cued (blinking) 2-not cued	CS(IT)
17.	Probability of a false positive being detected at a point where no valid target exists on the screen.	PFALSE
18.	Image enhancement feature indicator 1=yes 0=no	IENH

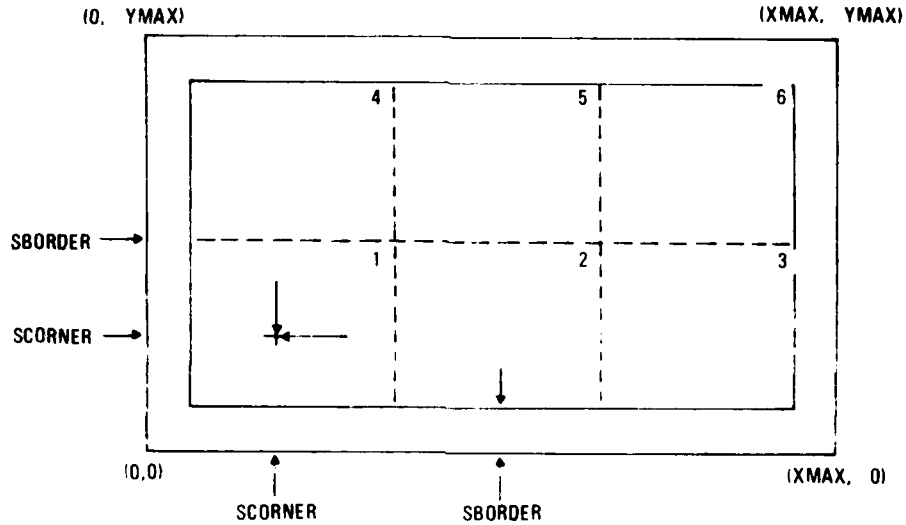


Figure 3-7. Model's Representation of CRT Surface.

Note that the presentation of data relating to the position and status of each target is provided by MAIN as input in Table 3-3, item 16. Accordingly, MAIN controls the appearance and disappearance of targets on the screen as a function of simulated mission time and other features of the simulation such as the speed of aircraft, dimension of the AN UPD-X viewing area, and the like.

SCAN DETECT LOGIC

Figure 3-8 shows the detailed scan-detect subroutine logic. *The five page flow chart shows each major* processing action including a brief description of the processing required and abbreviated programmatic statement(s). Data items not defined in the input list (Table 3-3) or the output list (Table 3-6) are shown in the list of other data items (Table 3-4).

In order to prevent an operator or other error from generating an arbitrarily long sequence of fixation points without limit (say in response to a "no target" situation), the subroutine counts the number of fixation points, using the variable MSC. If MSC equals the present limit MAXPTS (Table 3-2, item 12), then the subroutine sets the variable FLAG=1.

SCAN

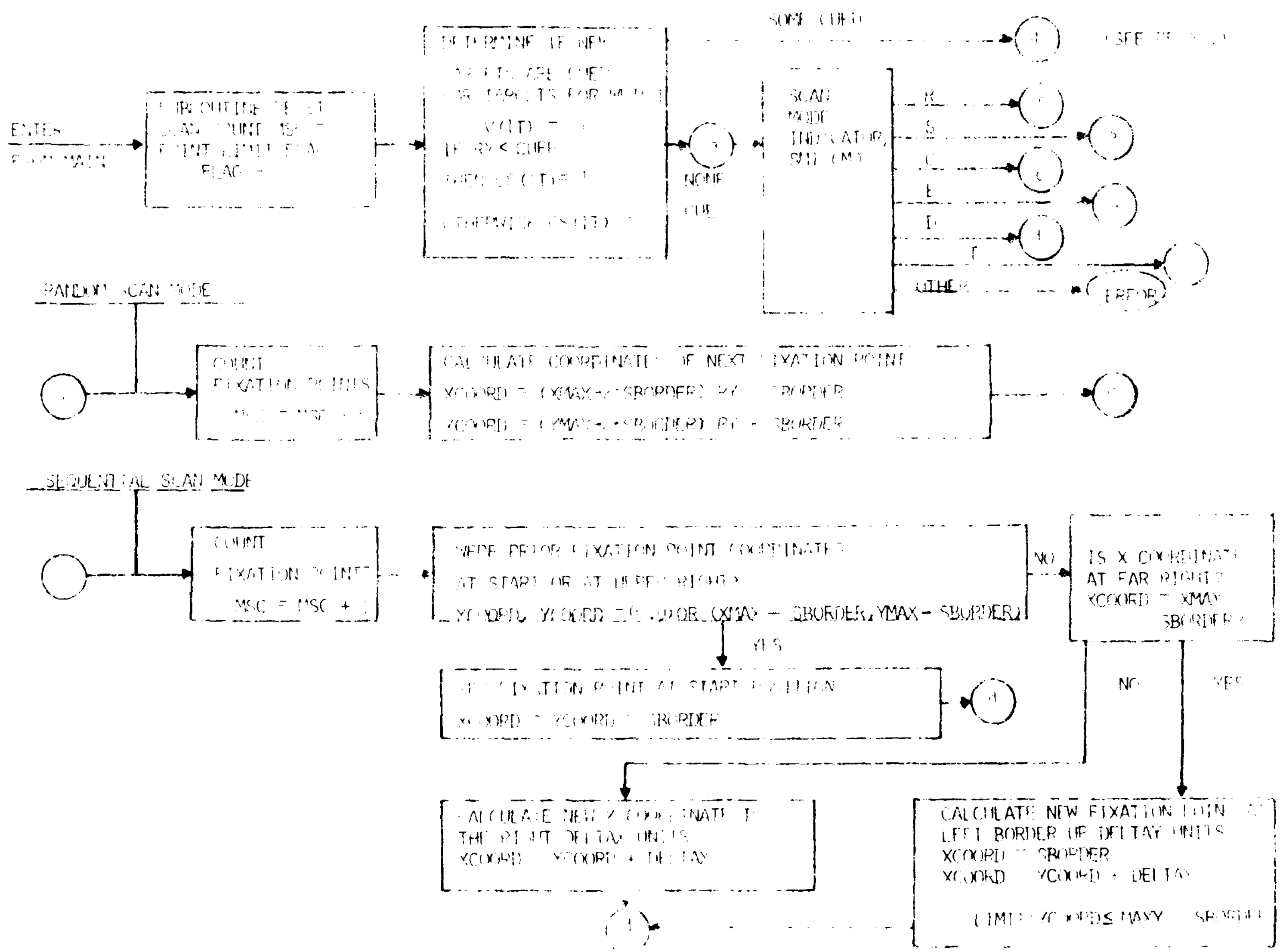
There is a different section of the flow chart for each of the scan modes designated by lower case letters corresponding to the six values of the scan mode indicator SMI(M).

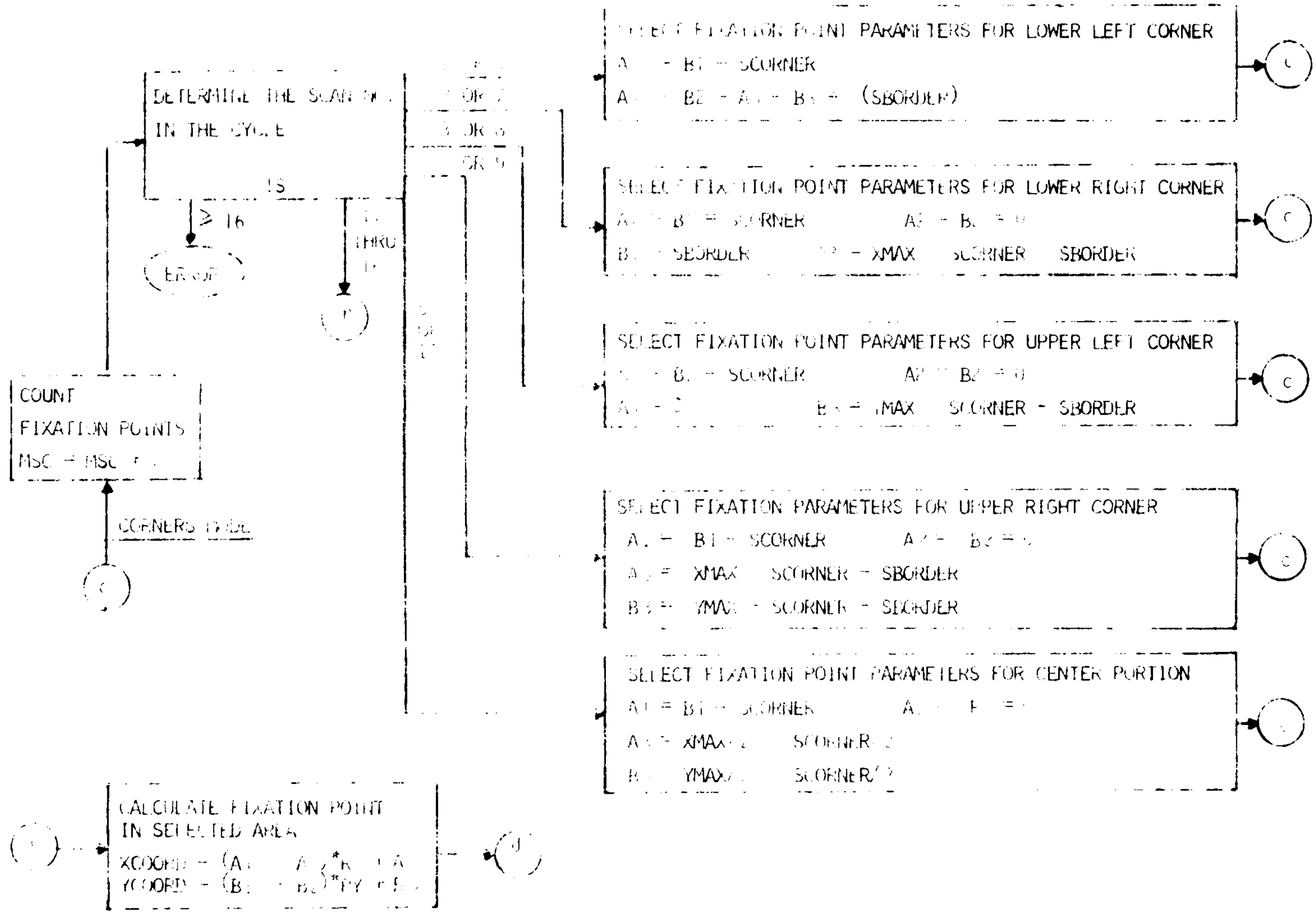
Table 3-5 is presented to summarize the method of determining the series of fixation point coordinates for each of the modes.

In each case, XCOORD and YCOORD are determined in accordance with the requirements of Table 3-4 and the coordinate system of Figure 3-7. When completed, the processing continues for any of the scan modes at circle "D" in Figure 3-8.

DETECTION

The target detection logic, starting at circle "D," is repeated for each target found to be within the prescribed circle, whose diameter is determined stochastically. First, all targets not previously detected are reset to status code 1 (item 16f of Table 3-3, DSC(IT)=1). This applies to targets currently having status 5 or 6. (Initially all targets will be set to status 0 by the MAIN program.) Those detected (code 2), classified (code 3) or processed by another operator (code 4) are not to be considered again for detection


ENTER
FROM MAIN
FLAG
SOME CUED
NONE
SCAN
MODE
INDICATOR,
R
S
C
E
F
OTHER
ERROR
RANDOM SCAN MODE
COUNT
FIXATION POINTS
CALCULATE COORDINATES OF NEXT FIXATION POINT
SEQUENTIAL SCAN MODE
COUNT
FIXATION POINTS
MSC = MSC + 1
WERE PRIOR FIXATION POINT COORDINATES
AT START OR AT UPPER RIGHT?
YES
NO
IS X COORDINATE
AT FAR RIGHT?
XCOORD = XMAX
SBORDER?
NO
YES
CALCULATE NEW FIXATION POINT AT
LEFT BORDER UP DELTAY UNITS
XCOORD = SBORDER
LIMIT: YCOORD ≤ MAXY - SBORDER



DETERMINE THE SCAN
IN THE CYCLE
≥ 16
ERROR
THRU
COUNT
FIXATION POINTS
CORNERS
POINT PARAMETERS FOR LOWER LEFT CORNER
SCORNER
(SBORDER)
POINT PARAMETERS FOR LOWER RIGHT CORNER
SBORDER
XMAX
SBORDER
SELECT FIXATION POINT PARAMETERS FOR UPPER LEFT CORNER
SCORNER
SCORNER - SBORDER
SELECT FIXATION PARAMETERS FOR UPPER RIGHT CORNER
SCORNER
XMAX
SCORNER - SBORDER
SCORNER
SBORDER
POINT PARAMETERS FOR CENTER PORTION
SCORNER
CALCULATE FIXATION POINT
IN SELECTED AREA
XCOORD
YCOORD

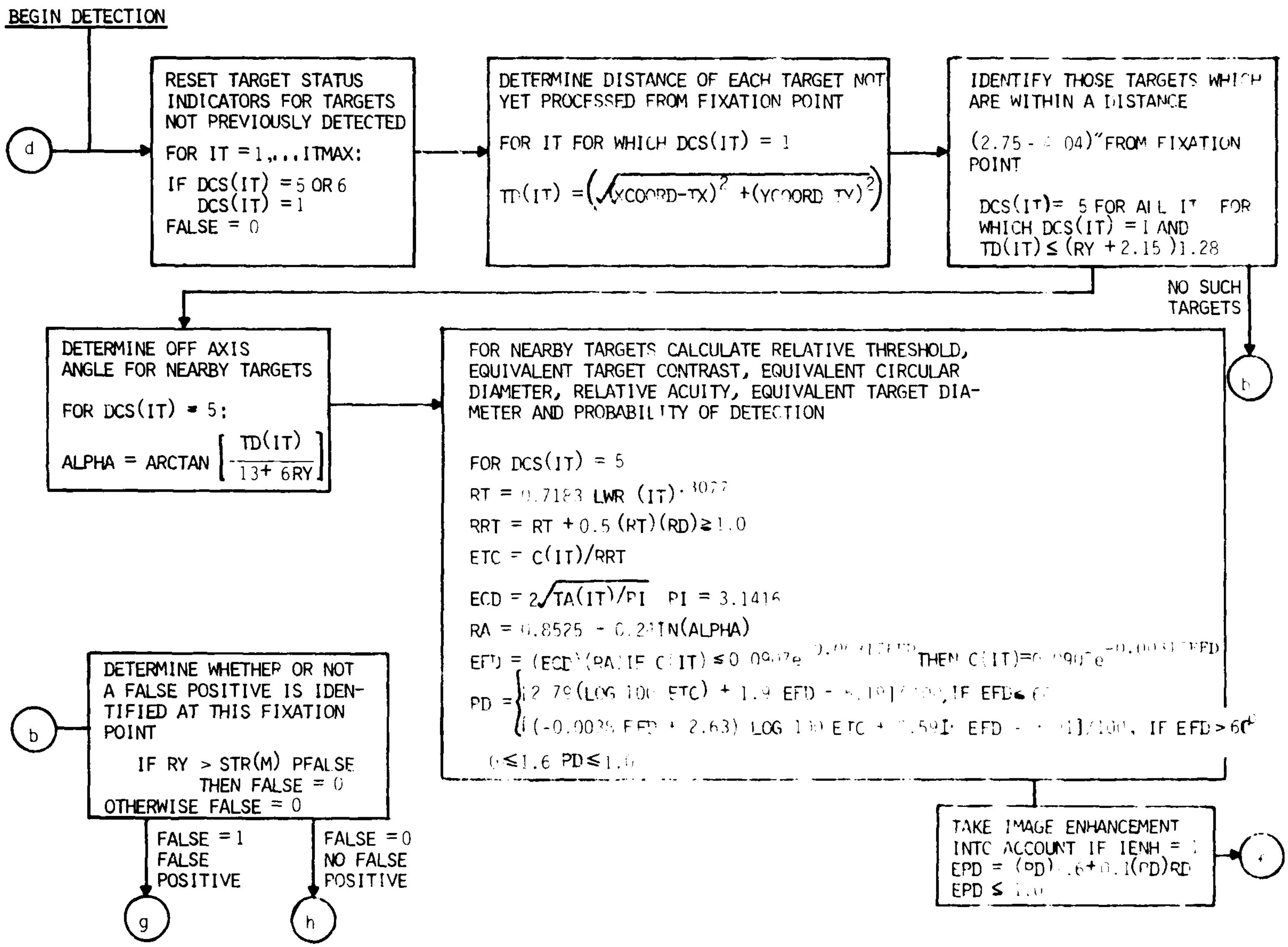


FIGURE 2.5 CONT.

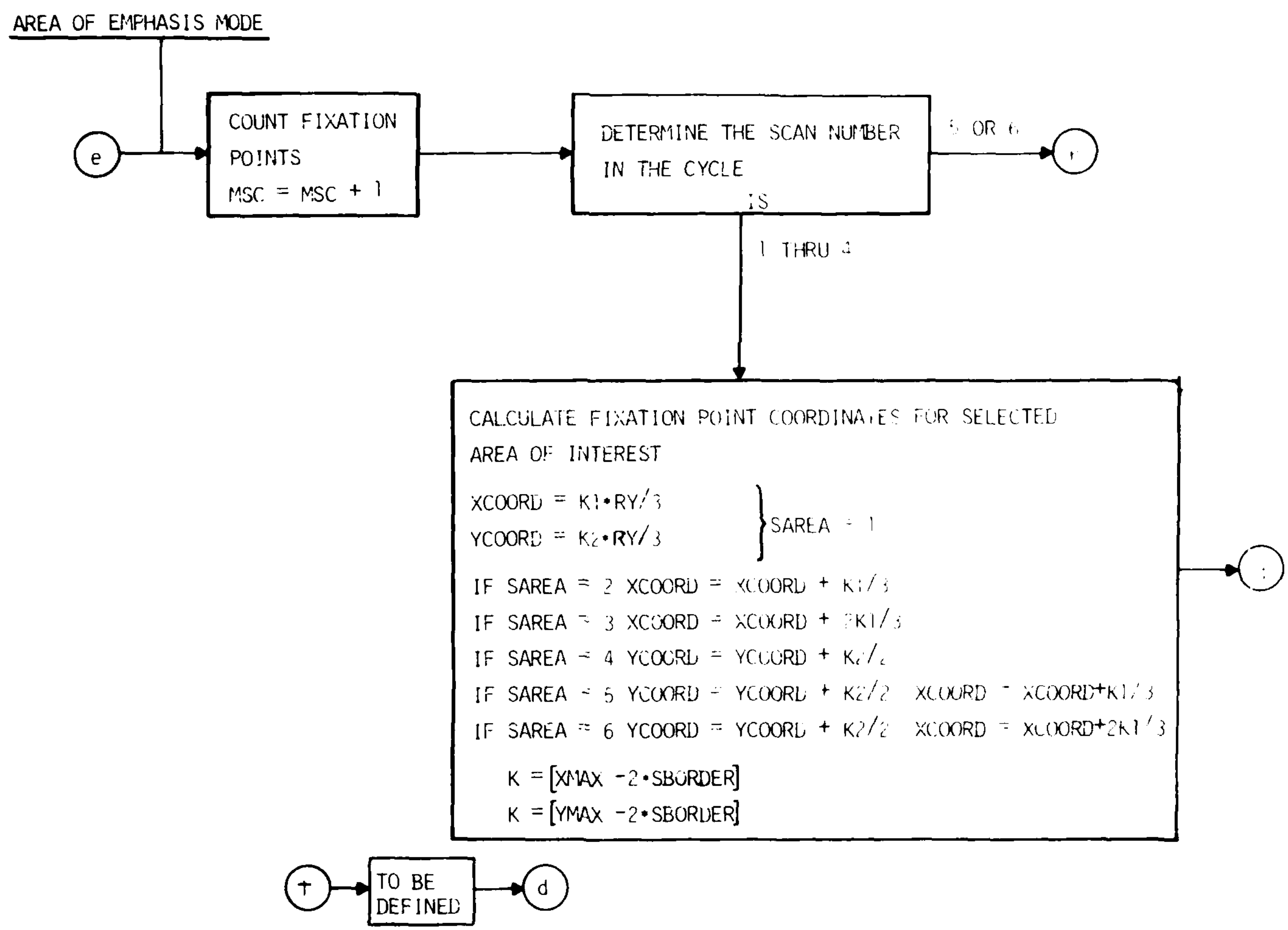


FIGURE 3-8. CONT.

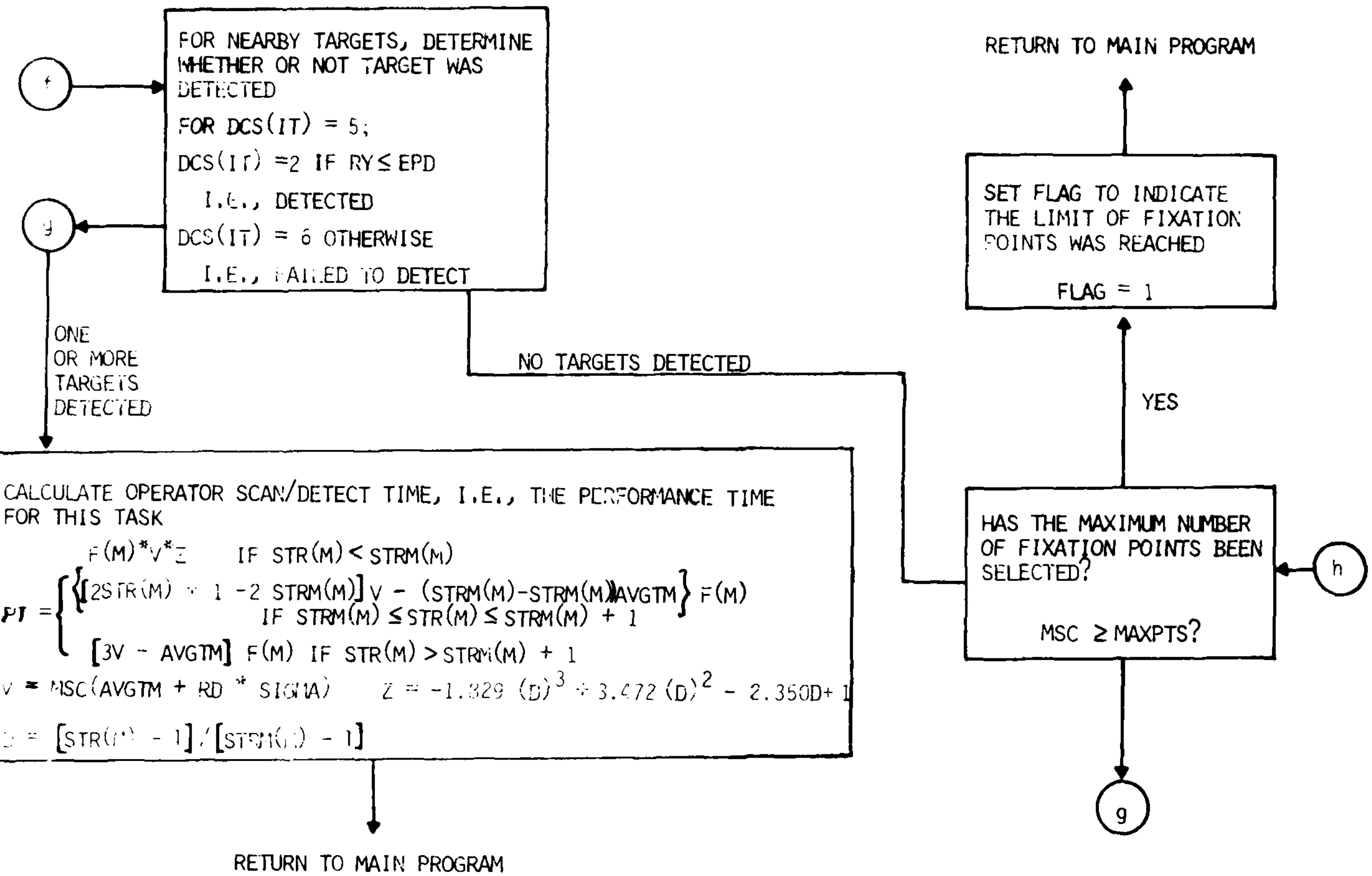


FIGURE 3-8 CONT

TABLE 3-4

OTHER DATA ITEMS

Parameter	*Data Name*
Module scan count, the number of fixation points selected per operator task (one entry of the scan module)	MSC
Pseudo-random number, equiprobable 0-1	RY
Pseudo-random number (avg.=0, sigma 1); i.e., random deviate	RD
Distance of target from fixation point	TD(IT)
Task performance time	PT
Flag indicating no targets found after checking the presented maximum number of fixation points (0=reset; 1=set)	FLAG
Relative detection threshold	RT
Equivalent circular target contrast	ETC
Randomized relative detection threshold	RRT
Equivalent circular diameter (minutes of arc)	ECD
Relative acuity	RA
Target off-axis angle subtended by eye between target and fixation point	ALPHA
Equivalent target diameter at fixation point (minutes of arc)	EFD
Probability of target detection	PD
Operator number	M
Target number	IT

TABLE 3-5

GENERAL DESCRIPTION OF SCAN MODE TECHNIQUES

SCAN MODE	*METHOD OF FIXATION POINT SELECTION*
RANDOM	SELECT XCOORD TO BE EQUIPROBABLE FROM SBORDER TO (XMAX – SBORDER) SELECT YCOORD TO BE EQUIPROBABLE FROM SBORDER TO (YMAX – SBORDER)

SEQUENTIAL

SELECT NEXT POINT TO BE DELTAX UNITS TO THE RIGHT. IF THE RESULTING POINT EXTENDS BEYOND THE RIGHT HAND BORDER, SELECT THE BORDER AS THE NEXT POINT. IF THE LAST POINT WAS ON THE RIGHT HAND BORDER, SELECT:

$$\text{XCOORD} = \text{SBORDER}$$
$$\text{YCOORD} = \text{YCOORD} + \text{DELTAY} \leq \text{YMAX} - \text{BORDER}.$$

IF THE LAST POINT WAS:

$$\left.\begin{array}{l}\text{XCOORD} = 0\\ \text{YCOORD} = 0\end{array}\right\} \quad \text{or} \quad \left.\begin{array}{l}\text{XCOORD} \geq \text{XMAX} - \text{BORDER}\\ \text{YCOORD} \geq \text{YMAX} - \text{BORDER}\end{array}\right\} \quad \text{then}$$

NEXT POINT IS:

$$\text{XCOORD} = \text{SBORDER}$$
$$\text{YCOORD} = \text{SBORDER}$$

CORNERS

SELECT NEXT POINT TO BE IN ACCORDANCE WITH THE FOLLOWING SCHEME WHICH REPEATS EVERY 15 CYCLES

SCAN	*Scan point randomly selected in*
1,6	lower left corner
2,7	lower right corner
3,8	upper left corner
4,9	upper right corner
5,10	center
11-15	anywhere on screen

limit all points to be within borders

AREA OF EMPHASIS

THE SCREEN IS DIVIDED INTO 6 SCAN EMPHASIS AREAS OF EQUAL SPACE. SELECT NEXT POINT TO BE IN ACCORDANCE WITH THE FOLLOWING SCHEME WHICH REPEATS EVERY 6 CYCLES

SCAN	*Fixation point randomly selected:*
1-4	in designated scan area of emphasis
5-6	anywhere on screen

limit all points to be within borders

DIRECTED

THE COORDINATES OF THE FIXATION POINT ARE SPECIFIED BY THE MAIN PROGRAM

OTHER

TO BE DEFINED

TABLE 3-6

SCAN DETECT SUBROUTINE OUTPUTS

	Output Data Items	*Data Name*
1	Performance time of operator task (Secs.).	PT
2.	Coordinates of fixation point near which at least one target is identified, i.e., current fixation point.	XCOORD, YCOORD
3.	Flag indicating that the maximum number of fixation points (MAXPTS) has been reached without identifying a nearby target.	FLAG
4.	Indicator that a false positive was identified at this point. FALSE = 1(Yes) = 0(No)	FALSE
5.	Target number of all targets(s) for which the scan detect subroutine has made a condition or situation change such as: (1) target identified as cued (2) target detected (3) target failed to detect	IT

In order to determine whether or not a target whose code is 1 is close enough, its distance from the current fixation point TD(IT) is calculated. Figure 3-9 shows the geometry of detection. The scan/detect program assumes that the distance between the eye of the operator and the screen is equiprobable from 13 to 19 inches, and the viewing angle is 12°. Thus, the scan module will select a value for the visual detection radius VDR on a Monte Carlo basis. For each target and each fixation point, a new value of VDR will be selected which is equiprobable in the range 2.76 to 4.04 inches, VDR=(RY + 2.15) 1.28. The detection status DCS(IT) is then set to active code 5) for all targets within the range. A similar geometric analysis is used for the off-axis angle, calculated next if there is a target within the visual detection radius. Here, the screen distance is the value of TD(IT) just calculated, the angle is ALPHA, and the side is again from 13 to 16 inches. Thus,

$$\text{ALPHA} = \text{ARCTAN}[\text{TD(IT)}/(13 + 6\text{RY})]$$

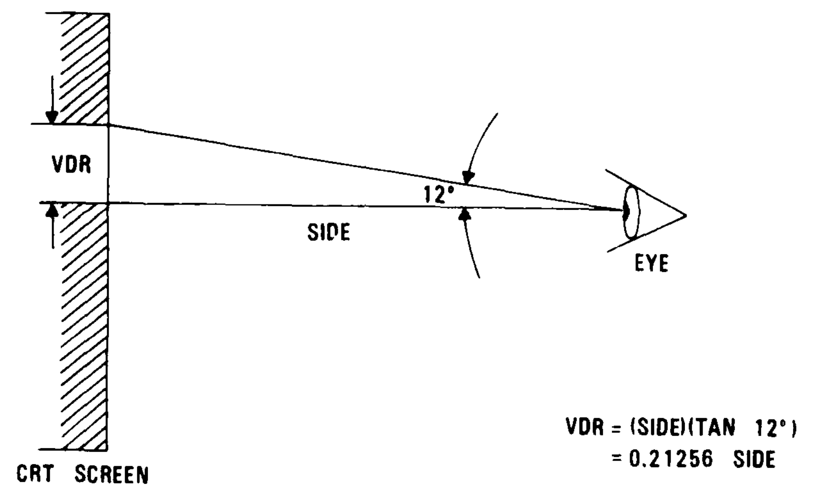
where RY is a random number equiprobable in the range 0 to 1. Where there are no targets within the distance, the next step is to determine whether or not a false positive is identified at this fixation point (circle b, Figure 3-8).

Following this, the detection probability is calculated for each target. The actual detection or failure to detect for each code 5 target is accomplished at circle "F" of Figure 3-8 by the comparison of a new pseudo random number RY with PD for each target. Detection is assumed if RY is less than PD. Detected targets are set to DCS(IT) code 2 and targets not detected are set to code 6.

The total performance time is then determined at circle "g" of Figure 3-8. For subjects who are nonstressed (STR(M)=1) and have average proficiency (F(M)=1), the performance time is determined stochastically so that in the long run the average will be a multiple of the average scan time, AVGTM. The multiple is the number of fixation points scanned prior to first detection or failure to detect a target, MSC. For example, if four fixation points were scanned before a detection and AVGTM=0.44 seconds, then the performance time, PT, would be 4 x .44 regardless of the number of targets. In order to introduce a stochastic element into the process of determining performance time the product of the standard deviation around AVGTM (SIGMA) and a random deviate is added to AVGTM to determine the total time. The important elements of stress for operator M, STR(M), his stress threshold, STRM(M), and his speed/proficiency factor F(M), are also considered by using the performance time calculation utilized in Siegel and Wolf (1969).

OUTPUTS

The outputs which the scan/detect subroutine makes available to the MAIN program are those identified in Table 2-6. Basically these are the performance time, the last (current) fixation point coordinate, a flag if the number of fixation points reached the limit, the indicator that a false positive situation occurred, and the target number of those targets whose status changed. This fifth output advises the MAIN program about the targets that are of immediate interest so that it can then, by examining the target data items (item 16, Table 3-3) determine future operator actions.



SIDE	VDR
13"	2.76
16"	3.19
19"	4.04

SIMILARLY: $\text{ALPHA} = \text{ARCTAN}\ \frac{\text{TD}}{\text{SIDE}}$

Figure 3-9. Detection Geometry

SECTION IV
CLASSIFICATION MODULE

This section and the following section present two largely independent designs for AN/UPD-X system target classification modules. The first was based on the concept of physical features of the targets to be simulated. The second, presented in Section V, is independent of such physical features and is therefore considered more desirable for application to the AN/UPD-X system because of its greater system specificity. The second subroutine is called the Alternate Classification Module.

Both classification subroutines assume that a specific target has been detected and both are concerned with: (1) the assignment of meaning to a target, and (2) the determination of the time required to assign the meaning.

The feature analysis approach utilized in the first classification subroutine resembles, in a sense, a Fourier analytic approach, and involves pattern generation for preselected primitive patterns in which the number of strokes in the primitive plays a key role. The probability of correct classification is determined in part as a function of the deviations of the target from its primitive.

A summary flow chart of the steps in this classification subroutine is presented as Figure 4-1. Figure 4-1 will be referred to throughout the subsequent discussion. The subroutine aspects concerned with time derivation (i.e., classification time) are discussed following the description of the classification logic. The section concludes with a presentation of programming aspects for modeling classification by the AN/UPD-X operator by a features analysis.

BACKGROUND

According to Shulik (Taylor et al., 1966) "a simulation of a system or an organism is the operation of a model or simulator which is a representation of the system or organism" (p. 2). "A computer simulation model is a logical mathematical representation of a concept, system, or operation programmed for solution on a high speed electronic computer" (Martin, 1968, p. 5). Such a representation is not construed to mean a counterfeit/specious structure, but a deliberate synthesis of real variables.

Available, therefore, is a technology for systematic inquiry into a set of real events whose salient dimensions have been abstracted and coded. But, confidence in the simulation is conditioned by the correspondence of the representation to the set of real events for which it is explicity intended—in this instance, the recognition of pictorial images which are generated by side-looking airborne radar. In developing the present model, the attempt was made to represent real events which have been identified as basic to the recognition/classification process in the experimental and the theoretic literature.

The "recognition of pictorial images" specifies and constrains the selection of meaningful parameters for the model. By their very nature, images constitute sensory abstractions of distinctive features of real objects. Images, as "departicularized" cognitive analogues to real objects, contain useful information about real objects, which can be conveniently stored and readily retrieved as the occasion may require. The model recognizes this abstraction and generates images on the basis of distinctive features and presents the simulated operator with a pattern of uniquely constrained, perceptible attributes.

Finally, recognition stipulates a past experiential familiarity with real objects: there is the explicit awareness of the real object having been sensed on a previous occasion. Through recognition an image can be retrieved from storage so that its information can be used in judging and reaching a decision about a here-and-now encounter. These attributes are treated within the model as context and operator ability variables.

The recognition of pictorial images is subsumed by a class of events/processes, variously called "pattern recognition," "form perception," "shape discrimination," and similar designations. "The term 'pattern recognition' has come to denote the detection or selection of objects in the environment which merit clas-

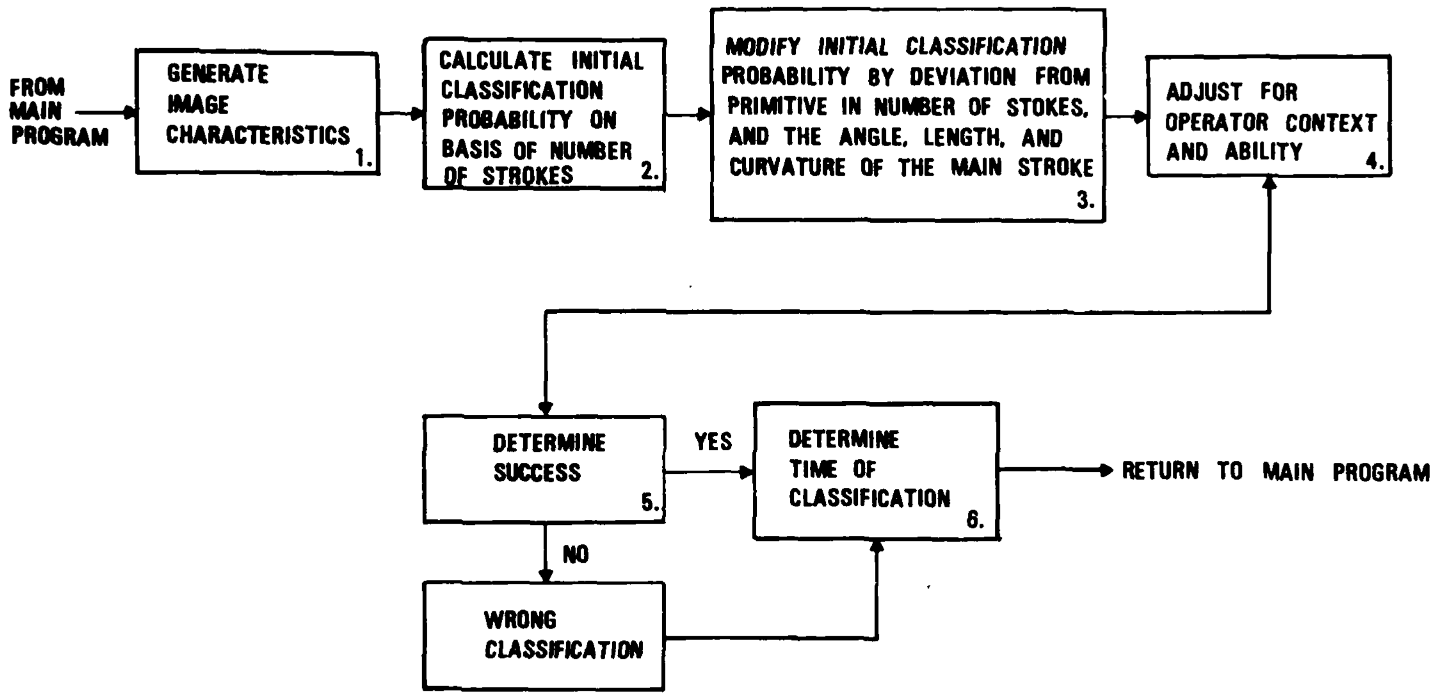


FIGURE 4-1. SUMMARY FOR THE FIRST CLASSIFICATION MODULE.

sification and the subsequent assignment of those objects to representative categories" (Brown and Aylworth, 1970, p. 203). Such a venture is not without challenging complexities. The capacity of the computer to manipulate efficiently variegated displays of patterns provides a ready vehicle for surveying and analyzing them. The theoretical potential and the experimental application of computer simulation models in the methodical probing of the multidimensional properties of pattern recognition for an improved understanding of the perceptual processes proper to pattern phenomena and for determining the ecological validity of the "artificial intelligence" attribute of such models have been critically examined and annotated by Gyr et al. (1966), Reed (1973), Uhr (1963, 1966, 1973), Wanatube (1969), and Zusne (1970). Notwithstanding the acknowledged usefulness of the computer in the clarification and resolution of psychological/behavioral issues, the essential passivity of a computer model with respect to a stimulus-display must be firmly differentiated from the active and selfcorrecting role of the human perceiver in pattern recognition. In this connection, the meaning of stimulus/cue/signal would be in accord with Dodwell's (Uhr, 1966) concern with the definition of stimulus, as an antecedent, and its relationship to a response. For, even though the purification of theoretical obscurities was not formally intended in this query, select theoretical formulations were necessary to satisfy the criterion for a computer simulation model for the recognition of pictorial images, as already postulated.

The recognition of pictorial images, as pattern recognition, accordingly, begins with a stimulus input of sense-data, which are physiologically mediated through the sense receptors and associated neural networks culminating in a cortical registration to result in a cognitive assessment in terms of a classification, i.e., to assign a name to the pattern. Without digressing into philosophical and psychological interpretations of perception, pattern recognition involves sequential transformation of information from one mode to another together with ordering it to preexisting memories so that learned responses can be promptly executed. Coherent wholes emerge. As a consequence, the categorization of an exemplar in its predesignated/correct class—a ship as a ship or an armored tank as an armored tank—can be expedited. Accuracy of classification is hereby implied, as well as the time to complete the classification successfully. The recognition of pictorial images, therefore, marshalls diversified experiences to direct expeditiously behavior/response in a prescribed context.

The efficiency of pattern recognition, and implicitly, the recognition of pictorial images, cannot be dissociated from the quality of stimulus input into the information processing system, be it human or computer. Recall that in the present case input in the real situation is the image resulting from side-looking airborne radar on reconnaissance missions for military intelligence. Jensen et al. (1977) detailed the technical superiority of this approach for the photography objects/targets of special interest. Brainard and Caum (1965) and Brainard and Ornstein (1965) stressed the importance of image clarity as a base for the extraction of viable information from aerially phtographed targets. It must be assumed, therefore, that enhancement techniques have been applied to the aerially photographed targets so as to improve the probability of accurate classification with maximal speed.

Image clarity, as image quality, suggests the presence of intentional structure in the stimulus for computer simulation. Such structure mandates a meaningful resemblance between pictorial image and photographic image, in contrast to the conventional research practice of using random polygons and other geometric designs, histoforms, and alphanumerical symbols in varying fonts, and other kinds of known objects. That is to say, stimulus input should not be unstructured/nonsense patterns. Its meaningfulness should be oriented to the objectives for which the computer simulation model is intended. In interpreting the results of familiarity judgments of nonsense patterns Arnoult (1960) noted that "It reflects only the obvious fact that the objects of visual experience are not a random sample of all possible shapes or forms. Rather, there are certain invariances in the forms of the real world and nonsense forms will be judged to be familiar to the extent that these familiar physical properties appear in them." (p. 266). Moreover, in assessing the results of studies into meaningful judgments of nonsense patterns Arnoult (1960) concluded that "Nonsense forms will be judged as meaningful to the extent that they embody the same physical characteristics which have come to be associated with meaningful objects in the real world" (p. 266). The advantage of the use of nonsense patterns in pattern recognition, thus, becomes dubious.

IMAGE GENERATION

With this background discussion in mind, it becomes obvious that a simulated form must be generated from each target (already detected) for which a classification is desired. In block 1, Figure 4-1, an image is generated for classification.

To this end, a set of primitives (Uhr, 1973), consisting of varying lengths of the line segments, degrees of angularity/slope including the horizontal and vertical orientation and degrees of convex and concave curvature, was prepared (Figure 4-2) to be used as the principal components in the construction of meaningful configurations. This selection of primitives faithfully reflects the cluster analysis of features in pattern design indicated by Gibson et al. (Reed, 1973). This selection also incorporates the distinction between structural (logon) and metrical (metron) content of data, proposed by McKay (Brown and Michels, 1966) where structural content refers to variation in feature like line segment, slope, and curvature, and metrical refers to variation in units for a feature like length of line segment and degree of slope. This selection, moreover, could be regarded as a population of features, samples of which were used, but not randomly, in the construction of meaningful configurations to accommodate Zusne's (Reed, 1973) criterion of a pattern, as "a configuration consisting of several elements that somehow belong together" (p. 4).

Each primitive/feature in Figure 4-2 was assigned a numerical index to specify its metric content. Consider first the line length (Figure 4-2(a)). In this case, the numerical index is 1; the longest line segment is assigned the numerical index of 7. The remaining numerical indices, 2 through 6, were assigned to the intermediate lengths of line segments. Similarly, in the subset of angles/slopes, the numerical index indicates the degree of angle, as legended. For example, the numerical index 4 indicates a horizontal orientation without slope; the numerical index 8 indicates a vertical orientation without slope; the numerical index 2 indicates a slope of 45 degrees in a right downward orientation, and the numerical index 7 indicates a slope of 45 degrees in a right upward orientation. Other numerical indices for angle/slope indicate the degree of angularity as well as the right-left and downward-upward orientation. The numerical indices can be similarly interpreted for the subset of curved primitives, where the numerical index 4 indicates an absence of curvature.

An infinite variety of real world type patterns may be generated from this set of strokes. Figure 4-3 presents examples of pictorial images, as patterns in Zusne's sense, assembled from the Figure 4-2 characterized strokes. The primitives in each pictorial image were ordered to resemble as closely as possible a real object/target. Each primitive image is coded with a numerical index for easy identification. (Note that these represent merely a sample set of primitives.)

Each image is composed of a collection of strokes, varying in number from 2 to 10. A frequency distribution of strokes per Figure 4-3 image is presented in Table 4-1. Fourteen of the images (70%) are composed of four to seven strokes. Three primitive images (15%) exceeded these limits in both directions.

Each stroke in an image is characterized by an element from each of the three subsets of strokes. Thus, length of line segment, degree of slope, and degree of curvature specify each stroke. Three numerical indices, listed in Table 4-2 are associated with each stroke. The first refers to the length of the line segment; the second refers to the degree of slope, and the third refers to the presence or absence of curvature. For example, the three strokes in image 1 are characterized as: 7-7-4, 1-1-4, and 1-11-4. The first set of three digits designates a very long line segment at an angle of 45 degrees without curvature. The second and third sets of three digits designate very short line segments which converge at an angle of 20 degrees without curvature. The two strokes in pictorial image 13 are characterized as: 6-8-4 and 6-8-4. Each set of digits designates moderately long line segments in a vertical orientation without curvature. A primitive-characterized stroke, thus, functions as an individual operator in determining the selection of elements to be considered for inclusion in generated image.

The use of individual operators in this fashion exemplifies an "analytical method" of pattern generation. Concerning such usage, Uhr (1963) noted that "a large number of separate analytic operations are performed on the input—operations of the sort 'is there a left concavity?' 'Is there an upper horizontal?' 'How many crossings does the pattern make with various lines?'...and these operators are satisfied not

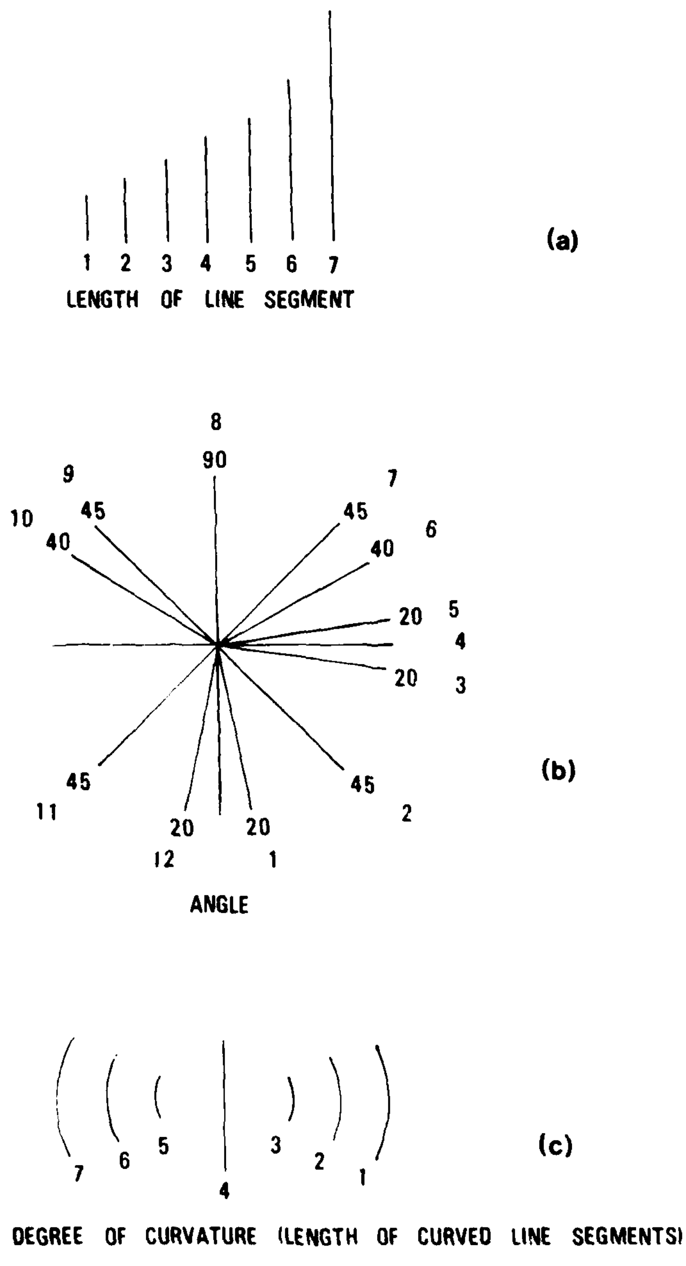


Figure 4-2. Primitive-Characterized Strokes Used In the Construction of Pictorial Images

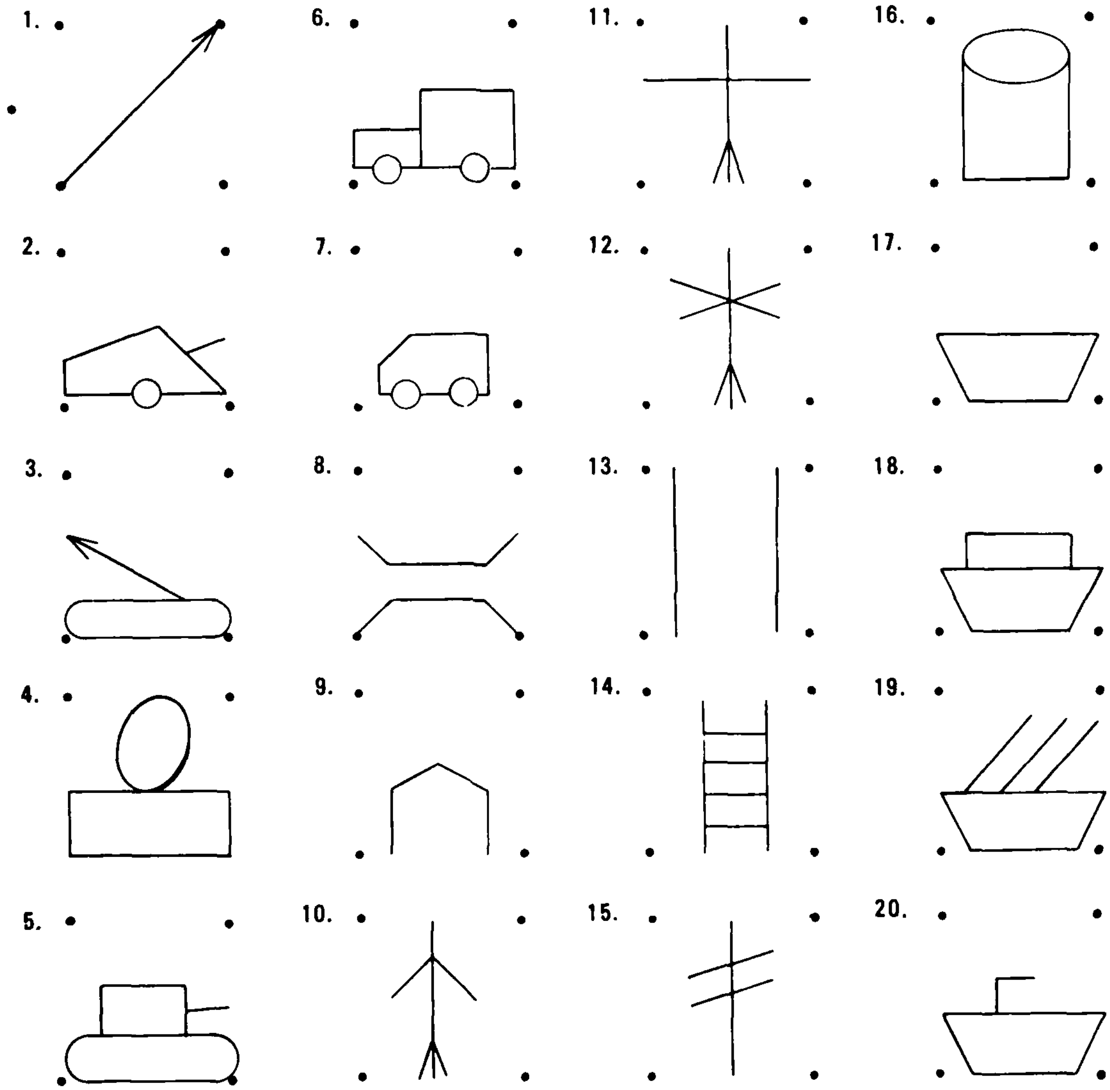


Figure 4-3. Sample Primitive Images Composed of Basic Indexed Strokes

TABLE 4-1

FREQUENCY OF STROKES FOR THE SAMPLE OF 20 PRIMITIVE IMAGES

Number of Strokes	*Frequency*
2	1
3	2
4	3
5	3
6	4
7	4
8	1
9	1
10	1

only by a rigidly placed input, but also by inputs over certain displacements, such as any curve anywhere within a specified section of the matrix" (p. 48). In effect, combinations of operators can be assembled to serve as a subpattern common to several pictorial images, e.g., the "dish-like" formation in pictorial images 17 through 20, characterized by the primitives in strokes 3-7-4, 3-9-4, and 4-4-4, or converging angular lines in pictorial images 10 through 12, characterized by the primitives in strokes 1-1-4 and 1-11-4.

IMAGE GENERATION LOGIC

Image generation takes place in block 1, Figure 4-1. The abbreviated logic for the generation of the image to be generated is presented in Figure 4-4. The images are generated from the strokes shown in Figure 4-2. Fuller detail on the integration of this logic into the subroutine is given in the section on subroutine implementation.

RECOGNITION

Once an image is generated, the problem becomes one of determining whether or not it is recognized correctly (blocks 2, 3, 4 of Figure 3-1) and how long it takes the system operator to make the classification. Classification pre-supposes discriminable patterns.

The efficacy of the classification strategy is contingent on the information abstracted and encoded from the specified primitive characteristics. In this respect, "Eleanor Gibson...suggested in a review of perceptual learning that a distinction could be made between theories of perceptual learning based on a template matching process and those based on the detection of features...The two main theoretical approaches on the problem of pattern recognition, according to Neisser are template matching, in which each new input is compared to a standard and *feature analysis,* in which the presence of particular parts of a pattern is decisive" (Reed, 1973, p. 11). Reed indicated the ascendancy of "features analysis" over "template matching" because of the flexibility of feature analysis and because it rests on structuring the stimulus pattern in terms of primitive-characterized strokes to correspond to environmental invariants.

The advantage of feature analysis is also reflected in Tulvig's "encoding specificity principle." According to Tulvig, specific encoding operations are performed on what is perceived to determine what is stored, and what is stored determines what retrieval cues are effective in providing access to what is stored (Tulvig and Thomson, 1973, p. 369). The relative strength of cues as features constituting the perceptual context at the time of learning is hereby emphasized.

Further, supporting evidence for feature analysis, as implicit to encoding specificity, is reported by Reed (1973) and by Phomson and Tulvig (1970). The observations of Caldwell and Hall (1970), Pick (1965), Posner and Keele (1970) and Reder et al. (1974) can be judged to be supportive in that perceptual conditions of learning contribute to the propriety of discriminative decisions on the basis of a feature analysis. In

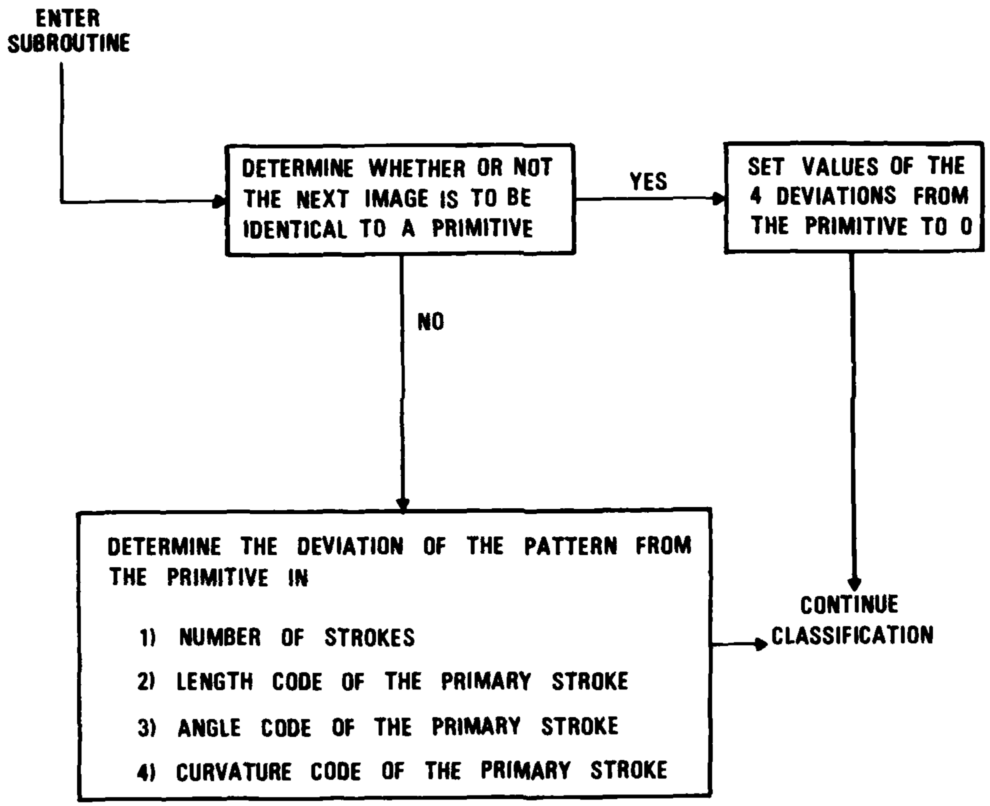


FIGURE 4-4. ABBREVIATED IMAGE GENERATION LOGIC

general, Tou asserted that "...feature selection has been considered as a key to the classification and recognition of patterns. Pattern recognition can be regarded as the categorization of input data into identifiable classes via extraction of the significant features of the data from a background of irrelevant detail...for practical pattern recognition systems, the determination of complete discriminatory features is extremely difficult, if not impossible. In general, only some of these features can be found. The classification scheme can be simplified by making use of these features and the available contextual information (Wanatabe, 1969, p. 505).

At best, the primacy of features over template matching/scheme or theory may be presupposed, insofar as geometric aspects of patterns—length of line segments, curvature, and slopes—incorporate salient features into the final global/holistic synthesis basic to generalization, which in turn, can operate to refine discriminative judgments about real episodes/events/ objects.

Specifically, the computer model calculates an initial classification probability (block 2, Figure 4-1). This probability is then successively modified to account for various figural, contextural, and observer experience training/aptitude effects (blocks 3 and 4, Figure 4-1). The details of the computer algorithm are presented in a later section on subroutine implementation.

First, the logic calls for determining an initial classification probability on the basis of the number of strokes in the generated target. This first approximation is based on the logic of Deese (Zusne, 1970) that "stimulus complexity and ease of identification appear to be related as a U-shaped function." That is to say, features can neither be too few or too many and neither too similar nor too dissimilar to expedite the recognition of pictorial images. The function employed in the simulation is presented in Figure 3-5.

Figure 4-5 was developed on the basis of the data presented by Levine and Eldredge (1974) who asked experienced photointerpreters to classify a set of already detected targets. Each target was presented on a light screen in frame form and circled. Varying amounts of ancillary information were provided and "difficulty" was also varied. The data of Levine and Eldredge indicate accuracy probability to range from .34 to .76 with an overall mean at .50.

This initial classification probability is then successively moderated (degraded) by four functions: (1) deviation from primitive in number of strokes, (2) deviation from primitive in angle of main stroke, (3) deviation from primitive in length of main stroke, and (4) deviation from primitive in curvature of main curved line, if any.

The first of these functions, deviation from the primitive in terms of number of strokes (Figure 4-6), is based on the conjecture that classification accuracy will degrade as the detail in a representation deviates from learned or anticipated detail. In a sense, a figure which is the same as a learned figure can be considered to be a structured stimulus. The influence of structure in form perception was acknowledged by Aiken and Brown (1971) who asserted that "Thus it appears that the O, in dealing with relatively weakly structured stimulus configurations, will impose a consistent structure of his own generation, to organize the stimulus configuration" (p. 282). Arnoult (1960) concluded similarly, as already noted.

Empirical image evaluative studies in which the amount of structure (learned detail) was varied also support this conjecture. Coluccio and Wasielewski (1970) varied image contrast and resolution in an investigation of photointerpreter performance with enhanced and nonenhanced equipment systems. Maximum completeness ([total correct = identifications/total possible components] x 100) ranged between 70 percent and 30 percent for the conventional method of viewing. The 70 to 30 comparison represents about 2.5 fold range. Similarly, MacLeod (1964) concluded after a photointerpreter performance study that "reducing image contrast, resolution or scale (within the ranges tested) leads to a reduction in the number of detectable changes." MacLeod reported identification accuracy to vary between 33 percent and 9 percent as a function of contrast. This represents about a fourfold range. Figure 3-6 was therefore constructed to represent a threefold range which is about midway between the MacLeod and the Coluccio and Wasielewski studies.

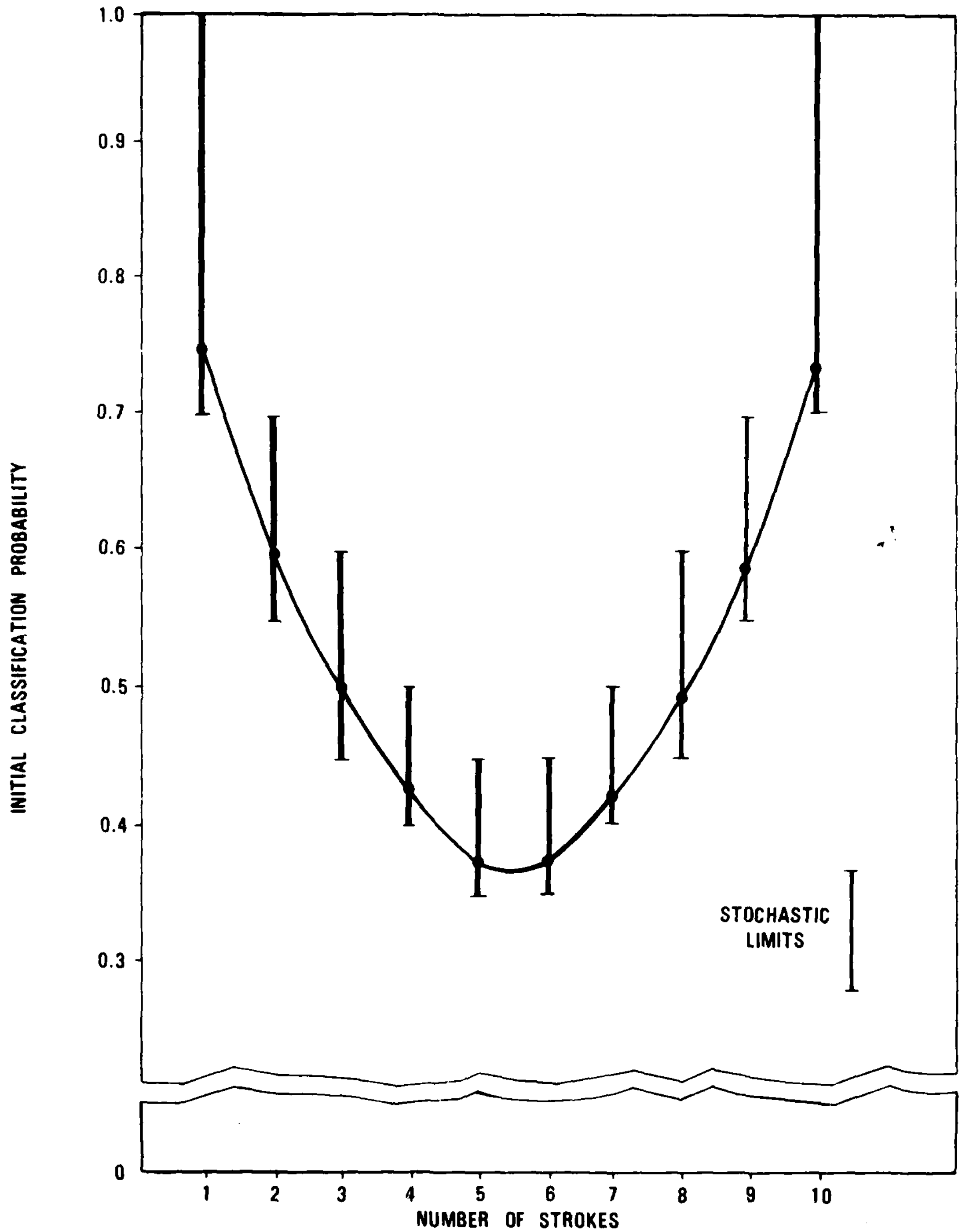


FIGURE 4-5. INITIAL CLASSIFICATION PROBABILITY AS A FUNCTION OF THE NUMBER OF STROKES IN GENERATED TARGET

The deviation from angle of main stroke function (Figure 3-7) rests on the argument that a shape rotated to a different position is less readily recognized when it is rotated as compared to the orientation in which it was originally learned. As stated by Hake,

> Actually, the fact that recognition of forms and comparative judgments of forms deteriorates when forms are rotated with respect to the observer has been known for a long time (1966, p. 151).

Hake reported a number of studies which support the contention of modified association value for slanted (rotated) figures.

The angle of rotation, however, is not linearly related to recognition and identification difficulty; shapes are recognized better in some orientations than in others, depending on their configuration and on the relationship of the axis of rotation to the main dimensions of space (Zusne, 1970). Zusne (1970) also considered "normal orientation" with respect to the retinal displacement from a customary orientation as well as the physical inclination of the observer's head. Accordingly, Oetjen (Zusne, 1970) reported that "recognition was good only when forms maintained their customary orientation with regard to the observer's retina" (p. 301). Hake (1966) confirmed that rotation can affect perception of form, and, implicitly, the recognition of pictorial images. The pertinence of rotation orientation of pattern is mandated by the probability that, in the radar photographing of military targets, it can be assumed that the tilt of the camera will not be constant/uniform over the flight path during a mission, thus producing inversions and other distortions of pictorial images.

In the present case, the results of Arnoult (1954) were relied on. Arnoult varied 10 nonsense shapes over 8 angular positions and asked subjects for judgments of same or different from a standard. The total range of errors was between 20 and 30 percent (a twofold increase) with some discontinuity in the data. Arnoult's data were smoothed and rescaled to develop Figure 4-7. However, the shape of the Arnoult curve was closely approximated over the mid range of Figure 4-7 and the twofold relationship was maintained.

The function, deviation from length of main stroke from the minimum (Figure 4-8) presupposes that subjective response alternatives increase as the target size decreases so that the match between current stimulus and mental template is more difficult. That is, guessing must be instituted until a correct "match" between stimulus-input and memory-pattern has been achieved when very small targets are involved. The constraints that preexist in the real environment need to be discovered through successive trial-and-error episodes, until stimulus features correspond to predefined pattern features sufficiently that the intended recognition response is obtained.

Bruns, Bittner, and Stevenson (1972) in a dynamic televisual identification task concluded that "Target effects were primarily related to target size expressed either as target area or target diagonal." Similarly, Steedman and Baker (1960) found search time to increase as target size decreased and Rusis and Snyder (1965) found target size to be statistically significant in a televisual study of recognition of air-to-ground targets. The same effect was found by MacLeod (1964) in an aerial photointerpretive study. And, Brainard and Caum (1965) reported an almost linear relationship between the size of the gap in a C and accuracy of perception in the position of the gap. The Brainard and Caum data indicated an approximate 4:1 increase in accuracy as gap size increased from .08 millimeters to .28 millimeters. To construct Figure 4-8, the Bruns, Bitner, and Stevenson target diagonal data were employed. Their data indicated an almost linear relationship ($r = .98$) between slant range identification and target diagonal with a slant range identification ratio of about 6:1 for "smaller" as compared with "larger" targets. Accordingly, Figure 4-8 was scaled to reflect a 6:1 ratio in a linear manner.

The fourth function (Figure 4-9), deviation in curvature, is similarly based on the contention that deviation from an anticipated image will decrease classification accuracy. The search initiated to retrieve information has been described, for example, by Checkosky (1971) as: "...the model of information processing in a memory search task presented...involves the following stages: (a) First, visual information from the incoming stimulus is passively registered. This information is then used to direct and verify the

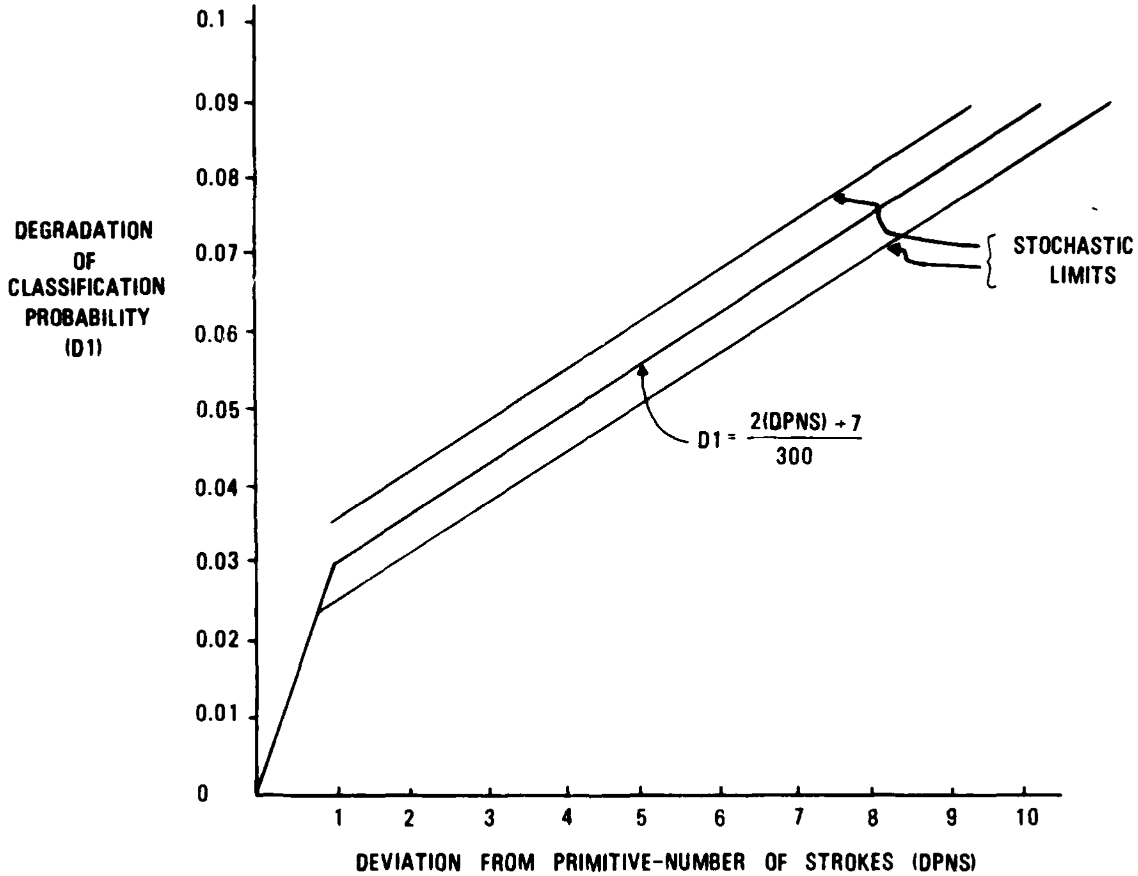


FIGURE 4-6. DEGRADATION OF CLASSIFICATION PROBABILITY
AS A FUNCTION OF DEVIATION IN NUMBER OF STROKES

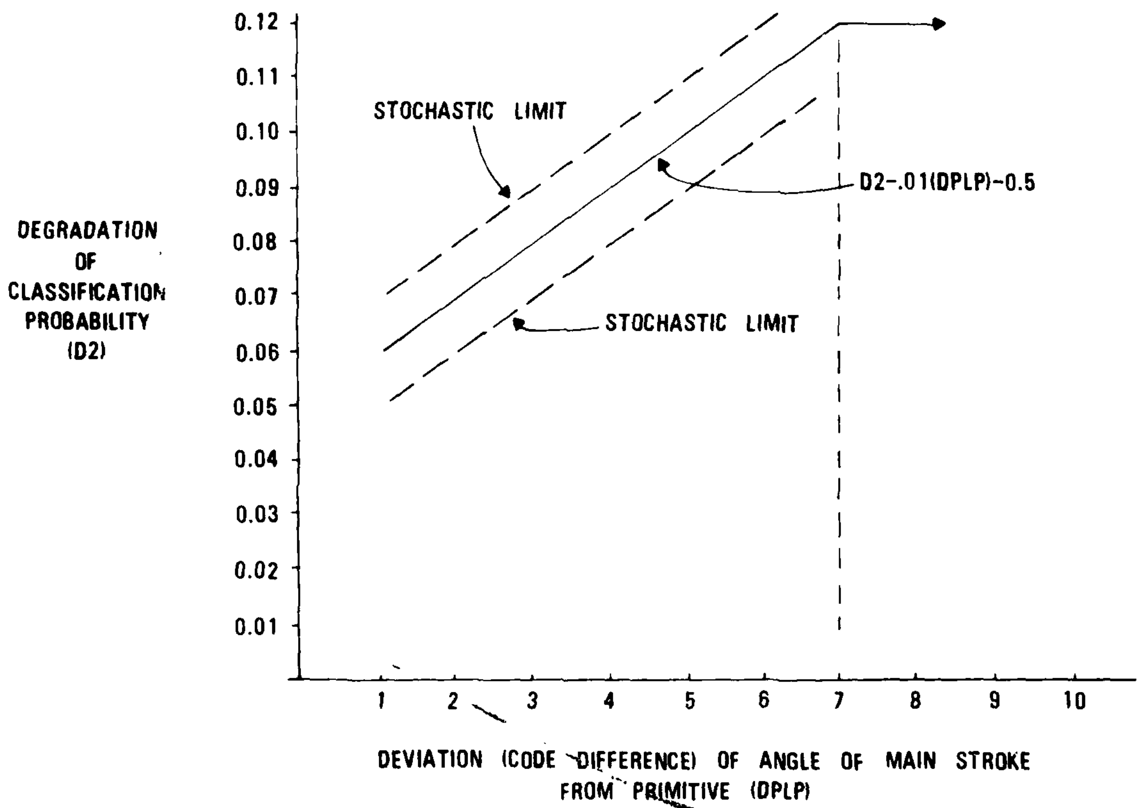


FIGURE 4-7. DEGRADATION OF CLASSIFICATION PROBABILITY AS A FUNCTION OF DEVIATION FROM ANGLE OF MAIN STROKE

subsequent memory interrogation. (b) Second, a visual code is generated for each of the items in the memory set. (c) Third, the visual code is then interrogated dimension by dimension. This memory interrogation does not involve a serial search through the memory set items. Instead, Ss apparently have direct access to that required information for each dimension. (d) Fourth, when sufficient information is obtained to allow the selection of a response, the memory interrogation terminates and the appropriate response is selected" (p. 388). Dumas and Grass (1973) outlined a similar proposal. Neisser (Reed, 1973) recognized the necessity for a stimulus examination as well as a memory examination phase for identification of the stimulus pattern. Paramount in the dynamic search, then, is sensitivity to a select stimulus here-and-now (perception), a comparison of that stimulus with previous experiences, and storage, followed by a classification judgment of "same" or "different," and, finally, the certification of that recognition through the verbalization of a preassigned name.

Unfortunately, no studies were identified which reported data relative to the effect of curvature on recognition accuracy. Accordingly, the Figure 3-9 curve was derived on the basis of the best professional judgment of Applied Psychological Services' staff members.

CONTEXT

The importance of context (block 4, Figure 4-1) to adequate classification is clearly evident.

The figure-ground attributes of context provides additional cues which may incline a person to one or another response in some instances and a categorical exclusion of a response in others. Accordingly, an armored tank would not be perceived as moving on a body of water. Context, thus, prescribes and proscribes the range of probable responses.

In contrast, our computer-generated patterns are context-free. A program of viable associations to represent a manifold of context codings would be prohibitive. It is conceivable that select "primitive-characterized strokes" could be included for classes of the generated images incorporated herein. To determine the degree to which the inclusion of "cues" could approximate the reality of diversified contexts would, however, require extensive study.

Unfortunately, "the matter of quantification of figure ground organization has not been really tackled by psychologists, although the concepts involved are clear enough to be operationally defined" (Zusne, 1970). In the present simulation, the data of Miller and his various co-workers were relied on. However, we note that Miller's work is based on semantic context. Generalization from a semantic context to a differentiated radar context may or may not be completely tenable. Certainly words and letters possess forms and there is little known about central nervous system processing which supports arguments that such forms are processed differently from pictorial representations. On the other hand, we do not seriously argue that the word "fox" looks like a fox. Regardless, both words and other representations possess what Miller calls "decision units" and context is assumed to reduce the number of such units.

Miller, Heise, and Lichten (1951) reported a range of context effects of zero percent to about 30 percent depending on the degree of context. They also found little additional gain from repetition. Their nonrepetition data are employed in the present simulation. Specifically, a random number between 0 and .30 is drawn and divided by two. This division is performed because we believe pattern context to be less influential than semantic context. The resultant is added to the current accuracy value.

OPERATOR PROFICIENCY AND STRESS

Finally, individual proficiency (block 4, Figure 4-1) in the recognition of pictorial images is a function of individual differences in feature selection and response biases. Aptitude variability and length of service in the activity of recognition of pictorial images are obvious contributors to such differences. Individual differences in encoding strategies condition mental sets, which, in turn, influence classification-recognition judgments, particularly, when stimulus conditions are not ideal. Thus, subjective expectations must be considered. To incorporate these considerations into the simulation, the classification probability is multiplied by an individual proficiency factor (provided as input) and a stochastic value is added to the product.

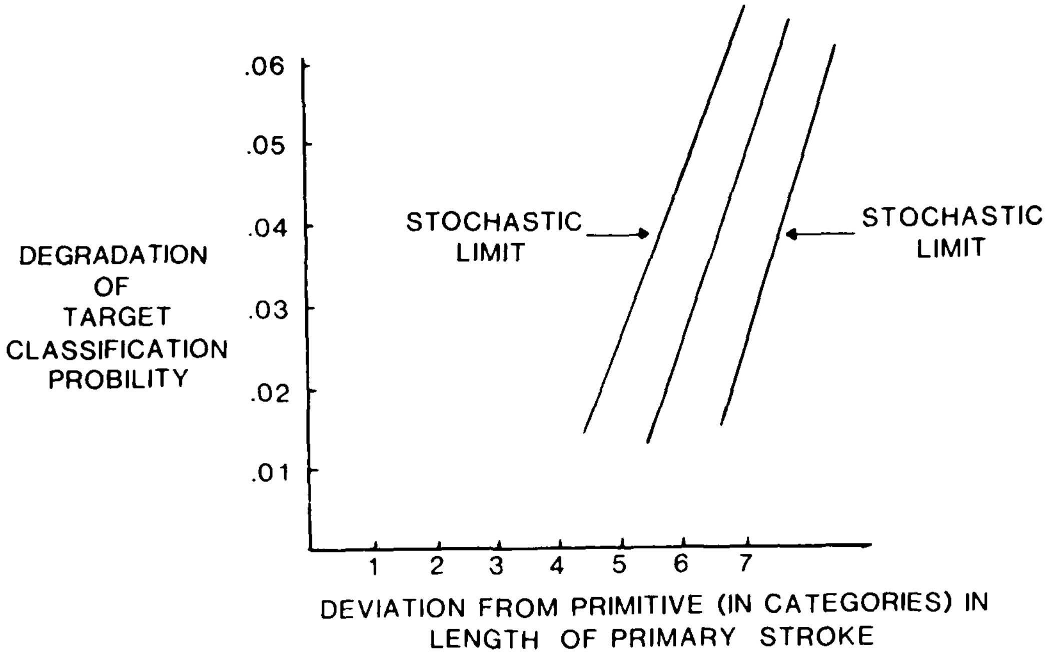


Figure 4-8. Degradation of Classification Probability as a Function of Deviation from Length of Main Stroke

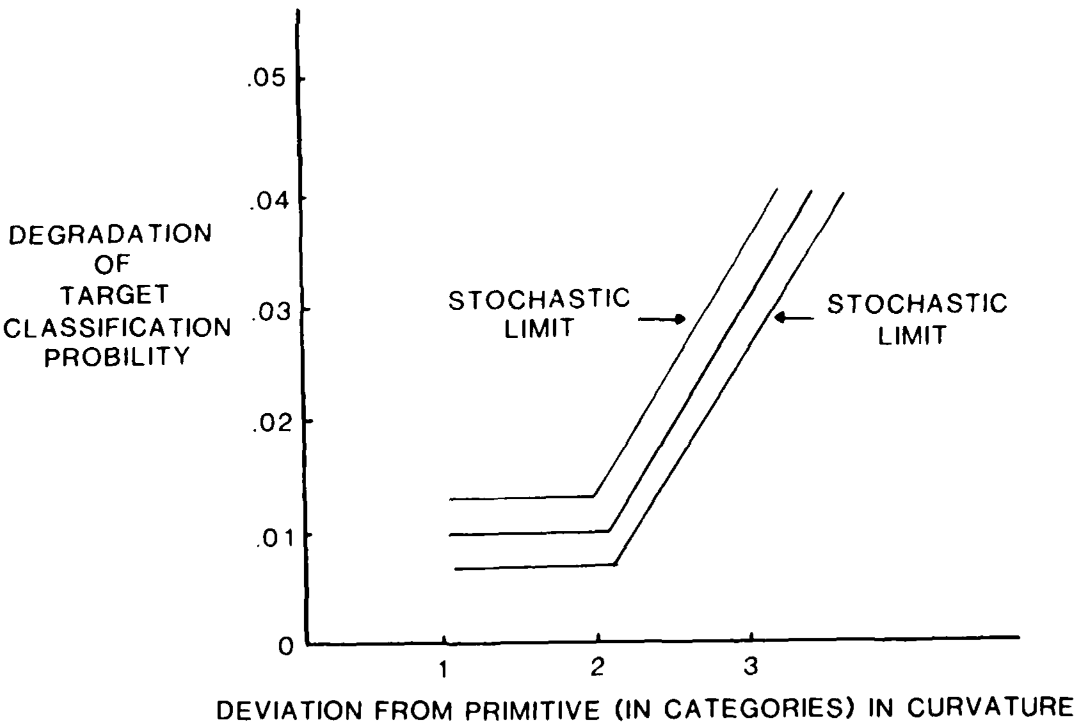


Figure 4-9. Degradation of Classification Probability as a Function of Deviation in Curvature of Main Curved Lines

Additionally, the effects of stress are accounted for. The stress function incorporated is the same as that which has been included in prior Siegel-Wolf models. Essentially, the stress function provides for an increase in accuracy as stress increases up to a point (called the "stress threshold") and then a decrease as stress goes above the operator's stress threshold (provided as input). The main routine tracks the operator stress.

CLASSIFICATION TIME

Accuracy judgments, however, are not sufficient in assessing the adequacy/efficacy of a classification-recognition scheme strategem in a practical simulation model. Information also needs to be processed speedily promptly without inordinate delays. Thus, time is a correlative variable with accuracy in the classification-subroutine.

In general, information processing variables that affect classification-recognition accuracy by way of ease or difficulty of completing the task can intuitively be expected to contribute to the time required for the reduction of uncertainty. If deliberation over response alternatives because of impediments to cognitive clarity becomes imperative, the classification-recognition response can only be delayed. Dumas and Gross (1973) reported that response times increased as accuracy was emphasized.

More specifically, illustrative investigations to support the contention of some covariation between time of classification-recognition and information processing variables associated with accuracy of classification-recognition are provided by Dick (1971), Dumas and Gross (1973), Dumas et al. (1972), Checkosky (1971), Nickerson (1967), and Nickerson and Feehrer (1964), who were principally concerned with the multidimensional aspects of stimulus-patterns, critical to effective categorization of stimulus-patterns. Kirsner (9173) observed that physical similarity of verbal stimuli facilitated the reduction of recognition time. Dick (1971), Hyman (Dick, 1971), Nickerson (1967), and Nickerson and Feehrer (1964) confirmed that response time increases with the number of features/attributes intrinsic to a pattern. "...it is apparent from the data that the number of attributes that the situation required be attended to did in fact affect categorization time, even if not in a simple and entirely consistent way" (Nickerson, 1967, p. 218). Fitts et al. (1956) proposed that recognition time is less for random patterns than for constrained/structured ones.

In the photointerpretive situation, MacLeod (1964) reported a rather extensive investigation in which recognition time was investigated as a function of identification completeness and identification accuracy. The results of MacLeod also indicated a relationship between his completeness dependent variable and response time.

Time for classification can accordingly be considered to be a function of most, if not all, of the variables which affect accuracy. Abstracting from MacLeod's data, the following effects of image variations on identification time may be suggested:

Variable	*MacLeod Figure No.*	*Range Effect (%)*
Contrast	3	10 to 20
Resolution	8	10 to 20
Scale	13	10 to 20
Complexity	16	50 to 75

Moreover, the MacLeod data suggest viewing time for recognition to be between 120 and 200 seconds—depending on image quality.

The time calculation is initially drawn from and based on the accuracy calculation. Recognition accuracy values in the range of .34 to 1.00 may be anticipated from the model. MacLeod reported recognition times of 120 to 200 seconds. Accuracy is treated as a reflection of image quality (contrast, resolution, scale, complexity.) Accordingly, the logic first rescales the previous accuracy calculation (which varies between .34 to 1.00) to an image quality scale which varies between zero and one. After making the transformation, a random deviate between ± 0.1 is added to the transformed score. This reflects the accuracy range generally found by MacLeod to reflect individual image quality effects. Next, recognition time is calculated. This time varies with the derived image quality value from 120 to 200 seconds (drawn from the MacLeod time as a function of scale image quality, and display method data; his Figure 10). Finally, this time value is multiplied by the input operator proficiency value to account for operator proficiency.

CLASSIFICATION SUBROUTINE IMPLEMENTATION

This section presents the programmatic requirements for implementing the techniques, described above, into an operational classification subroutine. The subroutine will perform the classification and related functions for a single target for each subroutine entry.

The input data required by the subroutine are shown in Table 4-2. It is assumed that a number of primitives (equal to NOPRIM) have been selected. The image "generated" may be identical to one of these primitives (with probability = P1). Operator speed, current stress, and stress threshold, previously utilized in the scan/detect subroutine, are also required. The data for specific primitive targets (item 6 or Table 4-2) includes four items (code IC = 1 through 4) obtained by counting the number of strokes, and selecting the proper characteristics from Figure 4-3 for each primitive.

The visibility indicator (Table 4-2, item 8) is the same as is used in the scan/detect subroutine. Item 10 of Table 4-2 consists of a 4 x 8 table of cumulative probabilities of each possible value of deviations (code differences) between the current target and a primitive. Item 11 includes a 30 element table of constants used to determine the initial classification probability.

Figure 4-10 shows the detailed logic flow of the subroutine. Each major logic element box contains a brief description of the operations required as well as an analytic statement of the programmatic procedure necessary to implement the functional element. Variables used in these calculations, not listed in Table 4-3 (inputs) are shown either in Table 4-3 (subroutine outputs) or in Table 4-4 (other variables).

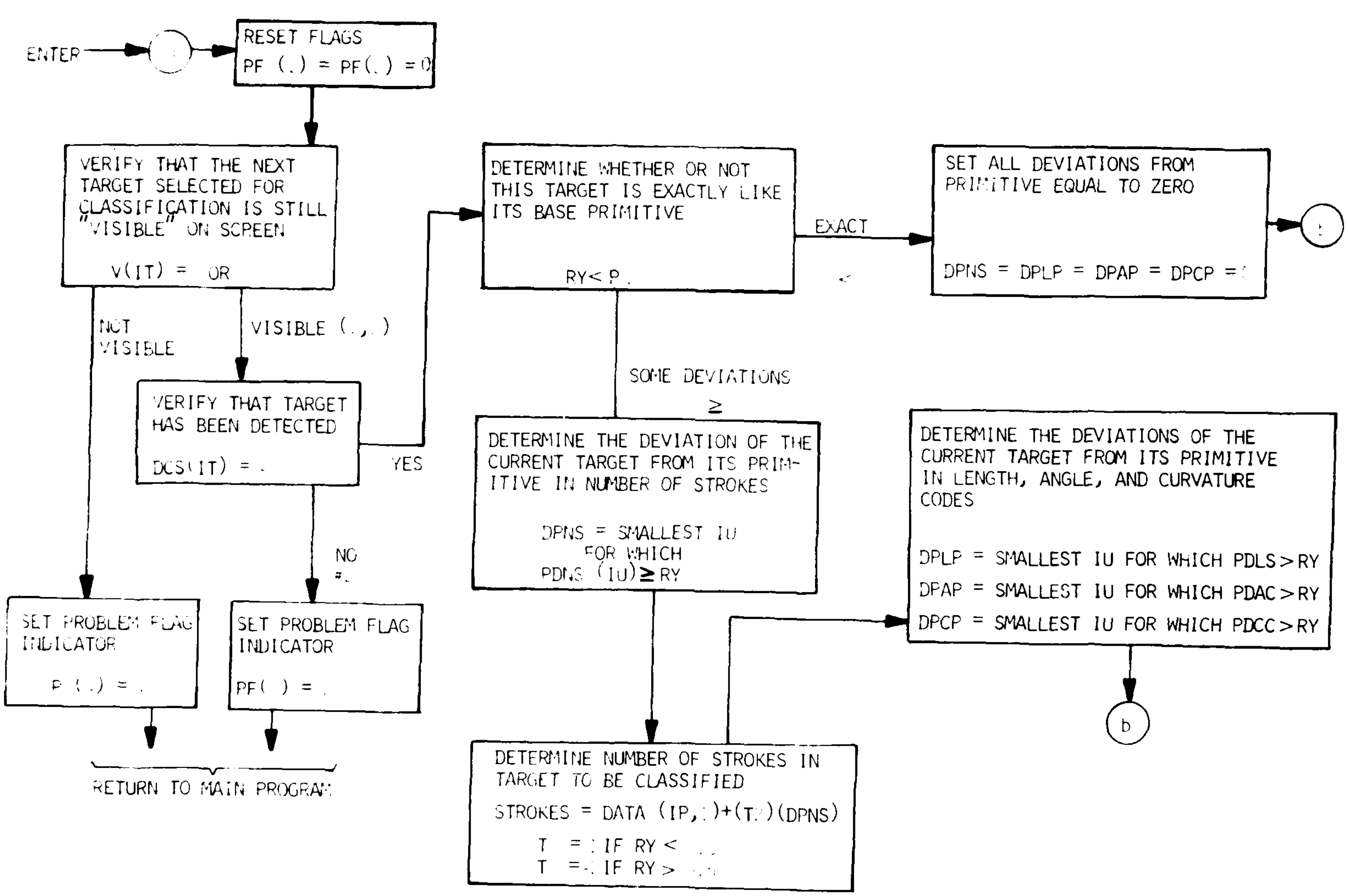


FIGURE . . . DETAILED SUBROUTINE FLOW LOGIC

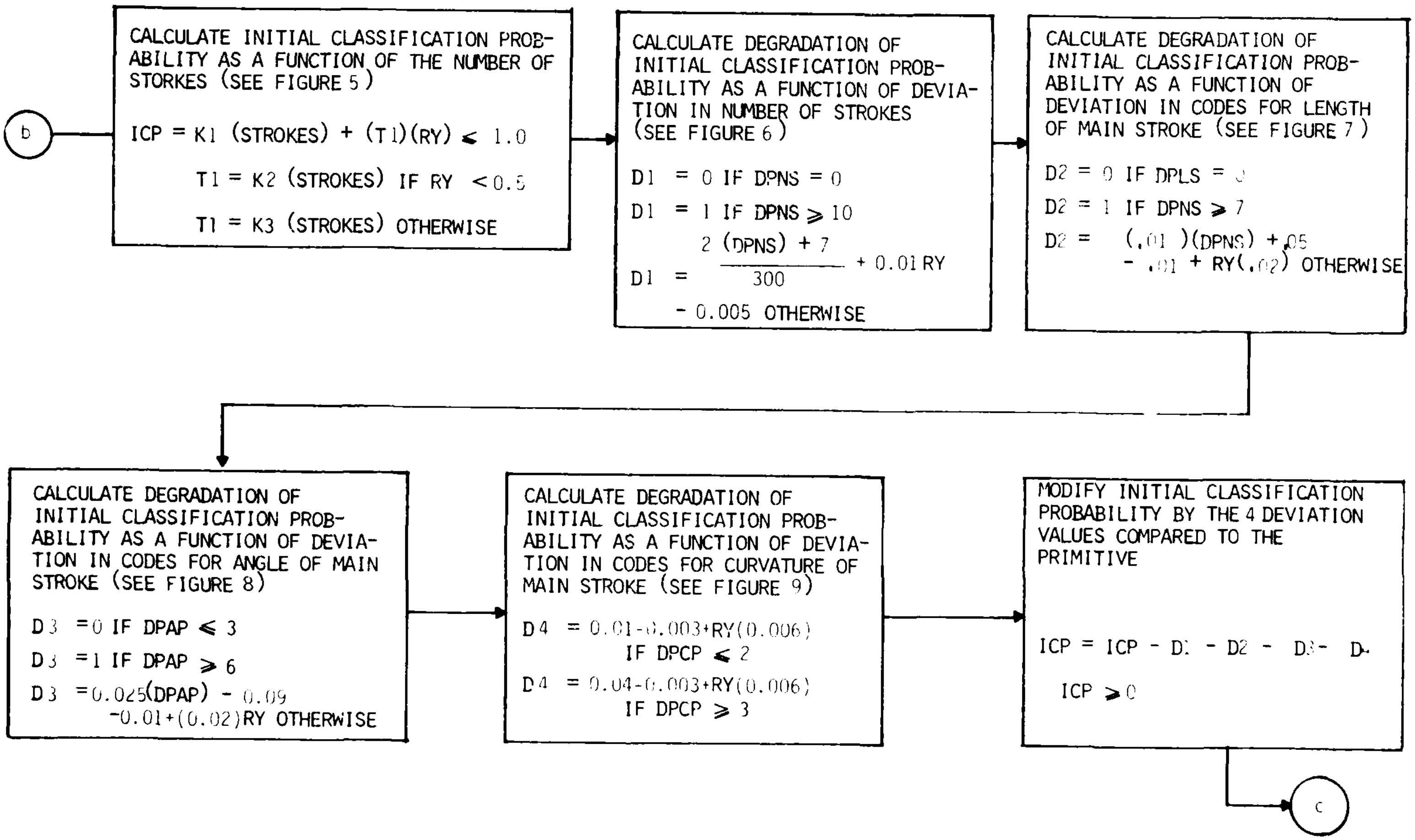


FIGURE 4-10. DETAILED SUBROUTINE FLOW LOGIC (CONT'D)

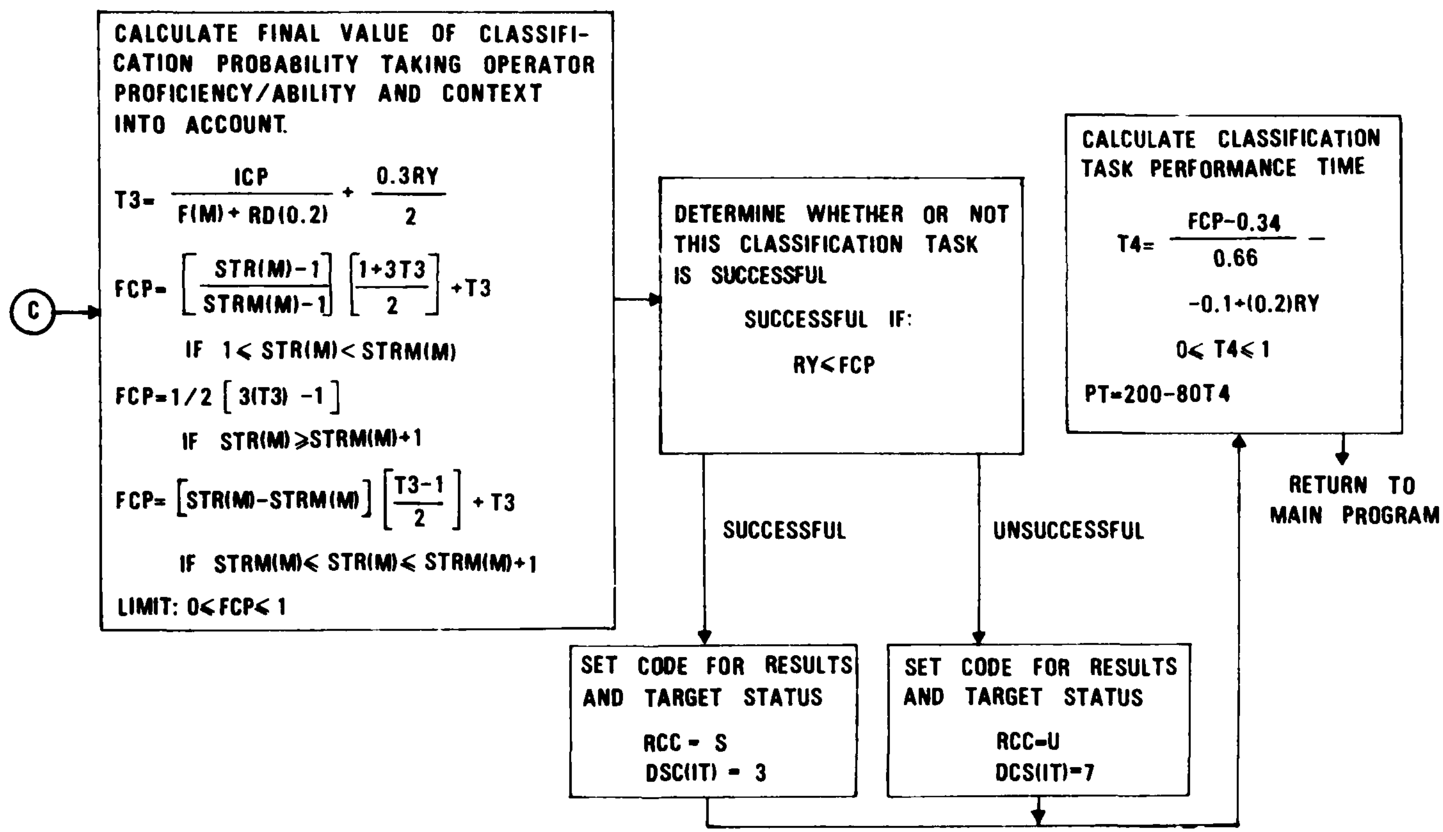


FIGURE 4-10. DETAILED SUBROUTINE FLOW LOGIC (CONT'D)

TABLE 4-2

CLASSIFICATION SUBROUTINE INPUTS

Input No.	*Input*	*Data Name*
1.	Probability of generating one of the primatives without change	P1
2.	Number of different prototype images	NOPRIM
3.	Operator speed (Proficiency) 1:nominal, ≤1:faster, ≥1:slower	F(M)
4.	Current stress value of operator M 1 minimum	STR(M)
5.	Stress threshold value of operator M,STRM(M) > STR(M)	STRM(M)
6.	Data for all primitive targets	DATA(IP,IC)

IC	*Data*
1	Number of strokes
2	Length of primary stroke
3	Angle code of primary stroke
4	Curvature code of primary stroke

7.	Number of targets to be classified	IT
8.	Target visibility indicator 0 — not visible now 1 — visible 1st time 2 — visible, not 1st time	V(IT)
9.	Type of target. A primitive number from IP=I to IP=OPRIM for every target IT	IT(IP)
10.	Cumulative Probability for Number of Deviations between Current Target and Primitive	

Number of Unit Differences	*Number of Strokes*		*Length of Primary Stroke*		*Angle Code of Primary Stroke*		*Curvature Code of Primary Stroke*	
	Prob.	*Cum. Prob. (PDNS)*	*Prob.*	*Cum. Prob. (PDLS)*	*Prob.*	*Cum. Prob. (PDAC)*	*Prob.*	*Cum. Prob. (PDCC)*
0	0.34	0.34	0.28	0.28	0.46	0.46	0.55	0.55
1	0.20	0.54	0.16	6.44	0.14	0.60	0.20	0.75
2	0.16	0.70	0.14	6.58	0.12	0.72	0.15	0.90
3	0.12	0.82	0.12	0.70	0.10	0.82	0.10	1.0
4	0.08	0.90	0.10	0.80	0.08	0.90	—	1.0
5	0.04	0.94	0.08	0.88	0.06	0.96	—	1.0
6	0.03	0.97	0.06	0.94	0.04	1.0	—	1.0
7	0.02	0.99	0.04	0.98	—	1.0	—	1.0
8	0.01	1.0	0.02	1.0	—	1.0	—	1.0

11. Data for initial classification probability (See Figure 4-5)

Number of Strokes	*Constants Required*		
	K1(Strokes)	*K2(Strokes)*	*K3(Strokes)*
1	0.750	0.250	-0.050
2	0.600	0.100	-0.050
3	0.500	0.100	-0.050
4	0.425	0.075	-0.025
5	0.375	0.075	-0.025
6	0.375	0.075	-0.025
7	0.425	0.075	-0.025
8	0.500	0.100	-0.050
9	0.600	0.100	-0.050
10	0.750	0.250	-0.050

TABLE 4-3

SUBROUTINE OUTPUTS

	Description	*Data Name*
1.	Performance time of operator classification task (secs.)	PT
2.	Results of classification S-successful U-unsuccessful	RCC
3.	Detection/classification status for target IT 1-no action yet 2-detected 3-classified successfully 4 5-used by scan/detect subroutine 6 7-classfied unsuccessfully	DCS(IT)
4.	Problem flag 1. visibility indicator not set 2. target not previously detected	PF

TABLE 4-4

CLASSIFICATION SUBROUTINE—OTHER DATA ITEMS

RY — pseudo random number equiprobable in the interval 0-1, different number each time called.

ICP — initial classification probability

FCP — final classification probability

DPNS — deviation from the primitive in no. of strokes

DPLP — deviation from the primitive in length code of the primary stroke

DPAP — deviation from the primitive in angle code of the primary stroke

DPCP — deviation from the primitive in curvature code of the primary stroke

D1 — degradation in classification probability due to deviation in no. of strokes

D2 — degradation in classification probability due to deviation in length code

D3 — degradation in classification probability due to deviation in angle code

D4 — degradation in classification probability due to deviation in curvature code

STROKES — no. of strokes in target to be classified

T1,T2,T3 — temporary variables

IT — Target number

As indicated in Figure 4-10, two checks are made at each entry to the subroutine. The first is a test to verify that the target is still in view. This is accomplished by a check of V(IT), a variable maintained by the MAIN program (see Table 4-3, item 8). If V(IT) has a value other than 1 or 2, it is not visible currently. The flag indicator PF(1) is set to 1, and control is passed back to the MAIN program. The second test is to verify that the current target (IT, Table 4-3, item 7) has already been detected. If not, the flag indicator PF(2) is set to one and control is passed back to the MAIN program.

Next, whether or not the target to be processed is to assume the exact pattern characteristics of a prototype is determined. This is to occur with probability P1. If this condition occurs (i.e., if a pseudo random, number RY, equiprobable in the range 0-1 is less than P1) then all four potential deviations from the prototype (i.e., number of strokes and length, angle and curvature of the primary stroke) are set to zero. If the current target is not identical to a prototype, these four deviations, DPNS, DPLP, DPAP, and DPCP are calculated. DPNS is determined by comparing the value of another RY with the set of eight PDNS values (Table 4-3, item 10). DPNS is set equal to the smallest number of unit differences (IU) for which PDNS (IU) RY. The number of strokes (STROKES) assumed to be comprising the target image is determined next by randomizing around the number of strokes given as input for the type of target selected [see Table 4-2, item 6, i.e., DATA (IP, 1)], given that target IT is a target like the primitive identified as IT(IP) (see Table 4-2, item 9).

The initial ralue of the probability of a correct classification (ICP) is calculated starting at circle "b" of Figure 4-10 and the final value of the probability (FCP) is determined at circle "c." The first selected value for ICP is determined as shown in Figure 4-5 as a function of STROKES. Following this, the four values of degradation (D1 through D4) are calculated in accordance with Figures 4-6 through 4-9, respectively. In each case, an appropriate band of uncertainty is incorporated using new values of RY. These four deviations are then each subtracted from ICP to yield a new ICP value. The final FCP is calculated as a function of operator stress, STR(M), operator proficiency, F(M) and operator stress threshold STRM(M). In doing this, a temporary variable T3 is determined to incorporate the effects of F(M) with a band of uncertainty of width 0.2 and to incorporate the effects of pattern context with an uncertainty band of 0.15. Here, a random deviate RD is used for the F(M) effect. RD is a normally distributed variable with mean zero and a sigma of one. The effects of stress and stress threshold are then incorporated as shown in Figure 4-11. If there is no stress (i.e., STR(M) = 1,) the value of T3 becomes the final probability FCP. If there is stress build-up but the threshold is not exceeded, then the value of FCP increases linearly beyond the value of T3 such that when stress reaches the threshold, FCP assumes a value halfway between T3 and 1 (certain successful classification). If the current stress exceeds the threshold, then FCP starting at a value of T3 begins to decrease (Figure 4-11) linearly until (when stress equals one greater than the threshold) FCP equals T3 less the same value used above (halfway from T3 to 1). Further increase in stress has no additional effects.

Given the probability of successful classification, the subroutine then determines success or failure by comparing this probability FCP with a new RY. If RY is less than FCP, the classification is successful and the results of classification code (Table 4-3, item 2) is set to S and the detection/classification status code (Table 4-3, item 3) is set to 3 (success). For failure RCC = U and DCS(IT) = 7.

The last calculation, performance or classification time is made in units of seconds using the transformations shown in Figure 4-12. Values of FCP from 0.34 to 1.0 are transformed into a variable T4 having a range from 0 to 1 while superimposing a randomization effect at a level not to exceed $\pm$0.1 [Figure 4-12(a)]:

$$T4 = \frac{FCP-0.34}{0.66} - 0.1 + (0.2)\,RY$$

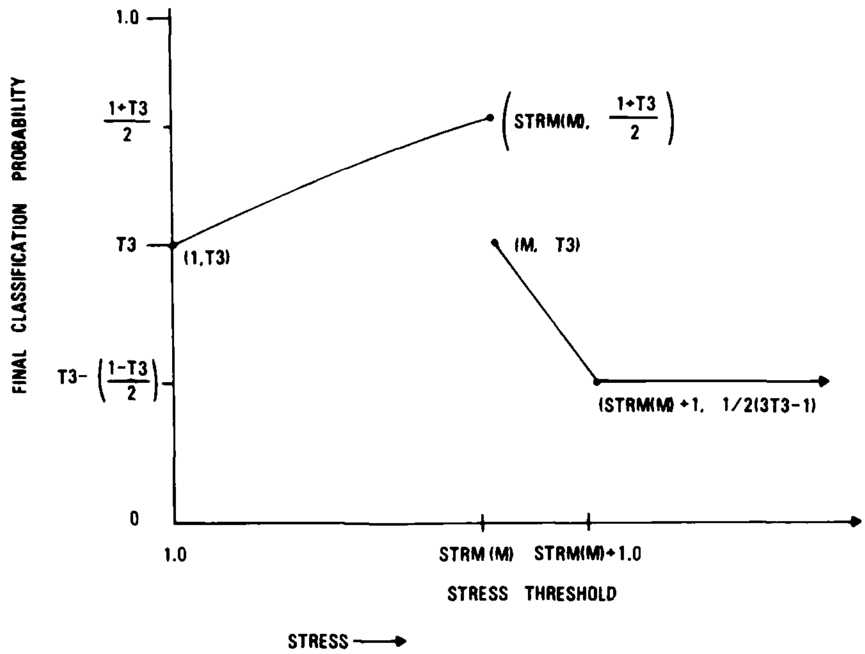


Figure 4-11. Effect of Stress on Classification Probability

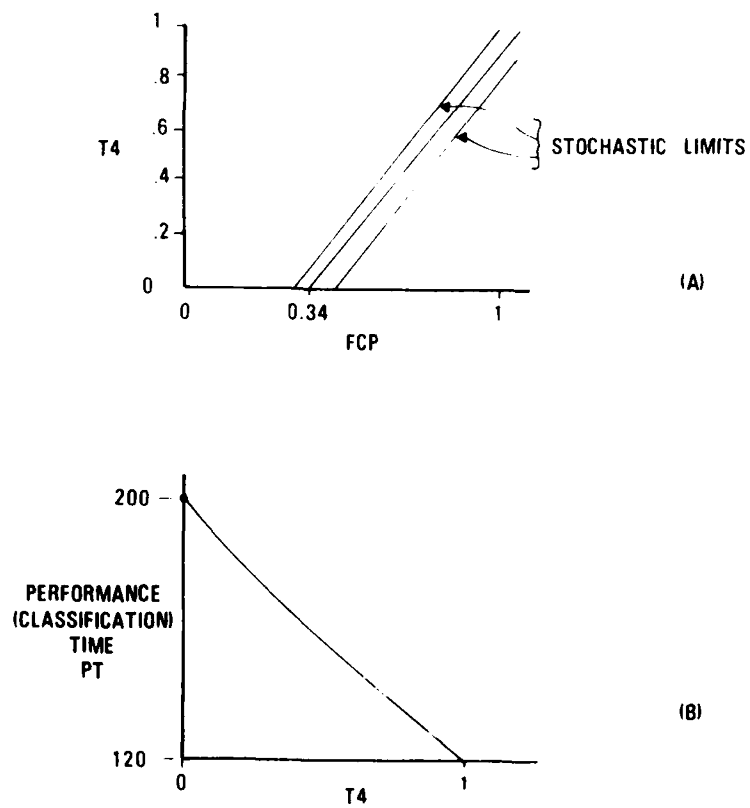


Figure 4-12. Transformations Used in the Performance Time Calculations

The variable T4 (suitably limited between 0 and 1) is transformed into the range of performance times from 120 to 200. This is shown in Figure 4-12(b) and is effected by calculation:

$$PT = 200\text{-}80\ (T4)$$

so that low probabilities of success FCP correspond to large performance times and vice versa.

DISCUSSION

Accuracy of classification/recognition of pictorial images is probably conditioned by such information processing variables as were included in the present simulation. A body of literature supports this contention. However, the question of the veridicality of the simulation must remain open because of the current state of the pattern recognition science.

That a dynamic processing does occur is not controverted. The operations proper to it, however, are. The dispute revolves around serial vs. parallel processing of information required for the delivery of the recognition response under appropriate stimulation. According to Neisser (Reed, 1973), features of a stimulus pattern are examined sequentially until sufficient information is on hand for rendering a decision. On the other hand, according to Sternberg, (Reed, 1973) who adapted Donder's (Sternberg, 1969) stages of cognitive processing, features of the stimulus pattern are scrutinized in parallel, thus achieving a synthesis to facilitate recognition of the pattern. Nickerson (1967) surmised that his results were ambiguous for defending either alternative. Reed (1973) reviewed in breadth and depth research inquiries pertinent to this issue, without a firm resolution for one or the other position.

Expediency, therefore compels a pragmatic choice. Predictors of a response are arbitrarily, but not capriciously, selected. Empirical testing follows to determine the validity of the selection. "...one has a hunch as to what features of a pattern an organism pays attention to, the appropriate measurements are taken, and a test—an experiment or a computer run—is made to see if they predict the response" (Zusne, 1970, p. 77). In this instance the decision was partial to a serial/sequential processing system because of its flexibility.

By way of conclusion, some contrasts between a computer simulation model for the recognition of pictorial images and its human counterpart need be considered. According to Zusne (1970), "The problem and it remains *the* crucial problem, is to formulate rules of decision in the *comparison* of the input information with some existing standards in the machine's memory. This involves (a) the specification of the structural elements in the pattern that must be used in the comparison, (b) the specification of how the comparison is to be done, and (c) the incorporation of learning rules to allow for the variations that are always encountered in a given pattern...Since the information that is fed into a computer must be exact and specific, the programmer must have an exact idea of the nature of discrimination and recognition processes, including the *principle of invariance*. Whether his ideas are right or wrong makes no difference to the computer, as long as they are exactly specified" (p. 75).

With respect to the principle of invariance Zusne (1970) argued that "the most important problem is the problem of invariance. It has not been solved for pattern perception by machines...If it had, there would be no need to write more programs...The reason is that the problem of how invariance is achieved in a living organism is still unsolved. Indications are that much more than repeated visual experience of the same pattern under different conditions is involved. A most important factor is kinesthetic feedback...as is the fact that form in everyday life is not a two-dimensional array of points but a surface or object and is perceived under continuous series of transformations as the perceiver moves in three-dimensional space. Reafference...is most certainly an essential variable contributing to the existence of perceptual invariance. Reafference...has not been incorporated in pattern-recognition programs in any important sense" (p. 84).

Through learning/training predesignated responses to preselected stimuli are acquired. In a practical situation, to maximize transfer from learning/training sessions to applied situations, stimulus materials can be expected to be highly comparable/similar. In accord with Tulvig's encoding specificity principle, retention and retrieval cues will be correlated. In this instance, in particular, the human operator/recognizer can avail himself of auxiliary aids, like earlier photographic records and display charts, to check the veridicality of his perception and the accuracy of his recognition judgment assessment. Uncertainty reduction, therefore, is not contingent solely upon a here-and-now stimulus-pattern.

Unlike a computer model, which is completely dependent on the designer for the content and for rules to be used in the selection and execution of a response, the human observer enters the learning/training schedule with a history of variegated experiences that can be profitably used to expedite the recognition of pictorial images. That is to say, he is not without internal resources by way of meanings, which can be associated with problematical patterns. Initiative, tempered by discretion, can be marshalled to assess the probability of the appropriate identification of a pattern.

SECTION V
ALTERNATE CLASSIFICATION MODULE

Modeling the cognitive aspects of target classification through processes involving features analysis and scheme rules, as described in the prior chapter, is appealing because the prior model appears to be in agreement with current theory. The prior model seems well in accord with the thinking, among others, of Gibson and Gibson (1955), Gibson (1966), Pick (1965), Aiken (1969), Franks and Bransford (1971), and Rosch (1973).

However, other approaches to modeling the behavioral aspects of the classification process are possible. One variant, such as that of Sternberg (1967), involves an information processing basis and postulates a high speed serial memory search which may be self terminating. Other, somewhat similar (Sperling, 1967) thinking postulates parallel processing with the features of each item being recognized sequentially.

Others (Rodwan & Hake, 1964) have applied discriminant analysis while Anderson's (1971) model of the classification problem employs cue validation and weights which represent the saliency of different cues or features. One class of models in this area—distance models—is based on a multidimensional scaling approach is relevant to establishing the perceptual aspects of the stimuli to be categorized, but more difficult to understand how the multidimensional scaling approach clarifies the cognitive/information processing aspects of the classification process.

Also, the pattern similarity (distance) models have been combined with choice models. Luce (1959) proposed a choice model which postulated both similarity and bias parameters.

AMBIGUOUS TARGET CLASSIFICATION

The fine resolution of targets, or potential targets on the CRT, such as those of the AN/UPD-X system, is often imperfect. System resolution, target aspect, camouflage, target range, and other factors may work to cause the reflected target image to lack the features necessary for a features or a scheme analysis by the observer. In such cases, the interpretation of an image may not depend on the objective characteristics of the image. Such features may not be available. A method is required which will allow modeling the classification of targets which are barren in distinguishing features. The choice model developed by Luce (1963) and later extended by Townsend (1971) seems to provide a basis for meeting this need.

LUCE'S CHOICE THEORY

In his exposition (Luce, 1963) of choice theory, Luce contended that response probabilities are of the form:

$$Pi(r|s) \quad \frac{a[s,t(r)]b(r)}{\Sigma a[s,t(r')b(r')]}$$

where:

scale a=the similarity between the presented stimulus s and the one, t(r), for which r is the correct response.

scale b=actual responses or a measure of response bias.

Accordingly, the probability of a given classification is a function of: (1) the similarity between the present stimulus and one which has been previously learned, and (2) the response bias of the observer.

The strength of Luce's model is that it considers both perceptual and response bias parameters. A difficulty with Luce's model is that it does not state the underlying processes which account for a choice. However, this concern is of minimal import in the present context.

TOWNSEND'S EXTENSION

Townsend was concerned with the confusion matrix generated by visual stimuli—in his case letters of the alphabet. He found the choice model to predict the confusion matrix (a matrix of the comparative confusability of various stimuli) as well as an overlap activation model and better than an all-or-none activation model.

The choice model developed by Townsend follows the formulation given by Luce and states that the probability (Cij) of response j when stimulus i has been presented is a function of the similarity between stimuli c and j and the bias value of the observer associated with response j. Specifically:

$$C_{ij} = \frac{v_{ij} B_j}{\sum_{k=1}^{n} v_{ik} B_k}$$

in which vij represents the similarity between the two stimuli and Bj is the bias value associated with response j. In the denominator of the equation, the products of the similarity and bias for all responses to stimulus i are summed.

In order to model the AN/UPD-X situation within this conceptualization, the similarity between stimuli would need to be determined for actual AN/UPD-X stimuli. Such an endeavor is not difficult to accomplish and the procedure would root the simulation directly to an actual scenario and to actual AN/UPD-X stimuli. Moreover, the similarity information would allow consideration of such AN/UPD-X features as image enhancement and coding techniques.

Response bias in the AN/UPD-X situation could be considered to be related to considerations such as prior operator training, briefing instructions, or intelligence information. For example, a system operator who was briefed on the fact that enemy deserters have informed our intelligence that SAM sites are in an area will be more apt to classify a suspected target as a SAM site.

We note that while such a formulation is, on the surface, free from a features analysis, the similarity data provided by experienced operators must come from one source or another. And, probably, they will base their perceptions on the stimulus features.

ALTERNATE CLASSIFICATION MODEL IMPLEMENTATION

For the alternate simulation of AN/UPD-X classification, we conceive of an AN/UPD-X operator confronted with a real time situation display on which he sees one or more figures called targets or stimuli. For the short time period which the subroutine simulates, this designated operator has no responsibility other than correct identification of the stimuli presented. This subroutine's goal is to simulate the operator in his classification of these targets—one target for each entry of the subroutine. During this processing, he will make a selection (here called a response) from among one of the 20 allowable types of target. The simulation will "determine" the validity of his selection and calculate the elapsed operator performance time.

Accordingly, the alternate classification model is designed to yield the results of classification (correct or incorrect), based on classification probability, and a classification time when degraded (featureless) stimuli are involved. The two output features, are common to all modules of the present series.

An overview of the alternate, target feature free classification subroutine is presented as Figure 5-1. Relative to correct classification correctness, the subroutine follows Townsend's conceptualization.

According to Townsend's conceptualization of choice theory, the probability of response to a stimulus is dependent on stimulus similarity and response bias. The subroutine calculation is based on an input matrix which represents the perceived similarity (freedom from confusion) among the targets which may be

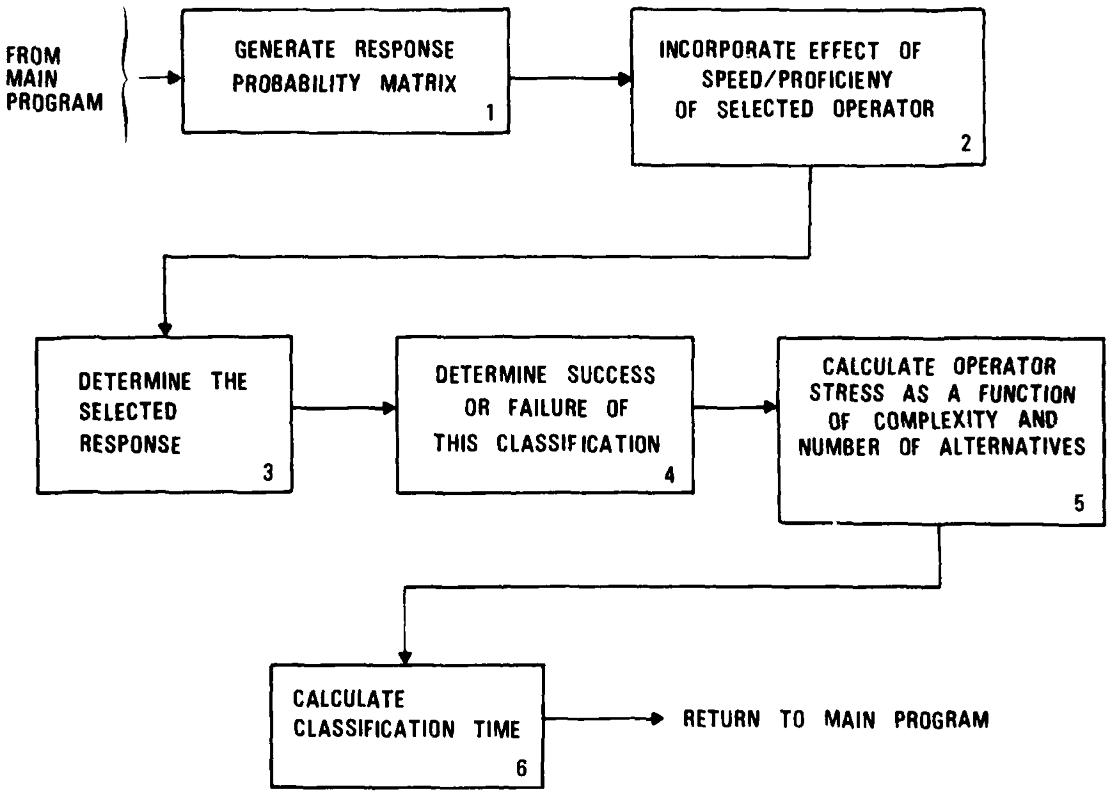


Figure 5-1. Overview of Target Feature Free Classification Subroutine.

of interest to the classifer. Up to 20 types of stimuli are allowed. Examples of stimuli are "tank," "aircraft," and the like. A simplified example of a similarity matrix, V_{ij}, for three real targets and noise (four targets) follows:

		Target Type			
		A	*B*	*C*	*D* (Noise)
Target Type	A	1.00	.75	.25	.85
	B	.75	1.00	.60	.25
	C	.25	.60	1.00	.10
	D (Noise)	.85	.25	.10	1.00

In the preceding matrix, diagonal elements are unity since each target type is obviously similar to itself. Also, stimulus A possesses high similarity to noise (0.85) and may be thought of as a camouflaged target.

The second required input is a response bias vector, which will be provided by the input analyst. Response bias values can range from zero to one. Zero indicates no bias for a given response to a stimulus. A response bias value of unity indicates a very high bias for a given response to a stimulus. For the four targets of the prior example, the response bias vector might appear as:

	Response			
	a	*b*	*c*	*d* (Noise)
Bias	.35	0	.25	.50

This distribution would represent a very conservative classifier, i.e., one who tends to favor responding noise rather than making a mistake, and one who rejects the possibility that stimulus B may appear.

With these two input data sets, a response probability matrix, C_{ij}, is generated using Townsend's formula (box 1, Figure 5-1). For the sample data presented above, the matrix appears as:

		Stimulus			
		A	*B*	*C*	*D* (noise)
Response	a	.42	.49	.23	.36
	b	.00	.00	.00	.00
	c	.07	.28	.65	.03
	d (noise)	.51	.23	.13	.61

The matrix is read as: the probability of response a to stimuls A is .42, etc.

Now, the effect of operator ability is superimposed on the matrix (box 2, Figure 5-1). To this end, the correct choice matrix probability is increased or decreased proportionally in accordance with the simulated operator's F (proficiency) value and the other matrix values are adjusted to compensate for the increase (or decrease) in the correct choice probability. This is accomplished by taking the product of operator speed, F, and each element of the response probability matrix to yield a modified matrix C_{ij}:

$$C_{ij} = F(C_{ij})$$

The next step (box 3, Figure 4-1), calculates which response is selected.

Given the known (correct) stimulus, C*, provided as subroutine input by the MAIN program, consider the corresponding column of the new response probability matrix, C_{ij}, i.e., C_{*j}. These response probabilities are then cumulated in order. Using the prior sample data, if stimulus B is selected:

$$\text{and } C_{Bj} = \begin{array}{c} \\ a \\ b \\ c \\ d \end{array} \begin{array}{c} B \\ \begin{pmatrix} .49 \\ .00 \\ .28 \\ .23 \end{pmatrix} \end{array}$$

Then the cumulative row vector is:

$$\begin{pmatrix} .49 \\ .49 \\ .77 \\ 1.00 \end{pmatrix}$$

A pseudo random number, equiprobable in the range 0 to 1, is then obtained and multiplied by the last (highest) such value, 1.0. The operator response (an integer response number) is then selected as the smallest row number for which the row vector element exceeds the product. For example, a random number of 0.58 will result in a selection of response row 3 since $0.49<0.58<0.77$.

Having simulated the selection of one response, the selected response is compared with the "correct" response, also provided as input by the MAIN program, in order to determine the simulated outcome of the classification—either correct or incorrect (box 4, Figure 1).

Note that the final choice may be: "noise" when a target is correct, target when "noise" is correct, or a misclassification.

CLASSIFICATION TIME

The prior logic provides information and module output relative to the classification choice and its correctness. The decision time logic is based on a separate logic which parallels, to some degree, the logic for the prior classification subroutine. Within the present module, classification time is based on stress, problem complexity, a basic time for making a classification in an N choice situation, and the number of target options available.

Stress is assumed to be related to both problem complexity and the number of response options available. Essentially, the decision, in which the correct response choice probability is significantly greater than other response choices, will impose less stress on the simulated AN/UPD-X operator then the decision for which the choices are about equiprobable. Similarly, a two choice classification will impose less stress than a many choice classification. For example, if the operator's classification requirement is to classify targets as tanks or not tanks (two choice), the decision is probably less stressful than the decision requirement to classify all vehicles by their specific type—say, tank, truck, jeep, automobile, armored personnel carrier.

RELATIONSHIPS AMONG PROBLEM COMPLEXITY, NUMBER OF DECISION CHOICES, AND STRESS

A problem of low complexity is assumed to be one on which the correct response probability is significantly greater than any other response probability. The highest response probability in the F adjusted response matrix is located and this probability is compared with all F adjusted probabilities in its row and its column. The mean of these up to 42 ratios ($C_{ij}/MaxC_{ij}$) is taken as the index of problem complexity. High values will indicate low complexity. The relationship between complexity induced stress and classification complexity is presented in Figure 5-2. To account for human variability, the stress value employed is stochastically selected from a distribution in which the average stress value is employed as the mean and the one standard deviation limits are those shown in Figure 5-2.

The relationship between the number of classification choices and stress is assumed to be logarithmic. A logarithmic relationship has often been shown to hold for psychophysical relationships. This relationship is presented in Figure 5-3.

TOTAL STRESS

Total stress is calculated by combining the stress due to complexity with the stress due to the number of choices available in accordance with the following equation:

$$\text{Total Stress} \quad \frac{1}{e^{(2\text{-CSTR-ASTR})}}$$

where:

CSTR = stress due to complexity
ASTR = stress due to number of alternatives

Total stress thus varies from near-zero (low stress) to one (high stress).

CLASSIFICATION TIME CALCULATION

As stated in the subsequent chapter on the decision subroutine, it appears as if decision time in laboratory studies is seldom less than .50 seconds and seldom more than 4.0 seconds.

The thought processes involved in the multistage decision processes are considered quite similar to those involved in the classification of an object from among a set of alternative choices. Therefore, the same Monte Carlo approach as that employed for the decision subroutine is selected for classification time determination here. A random number is selected from a normal distribution between .50 and 4.0 with a mean of 2.25 (center of range) and a standard deviation of 0.6 (about one third of the range). This random number is multiplied by the number of alternatives and by the operator speed factor to represent total classification time. The product is treated by the percentage time increase due to stress to derive the final classification time (box 6, Figure 5-1). The assumed relationship between stress and classification time increase is presented in Figure 5-4. This time calculation parallels that included in the decision subroutine, in that it involves the Monte Carlo factor in the 0.5-4.0 second range, the number of selection alternatives, and an increase in the presence of total operator stress.

PROGRAMMATIC ASPECTS OF THE ALTERNATE CLASSIFICATION SUBROUTINE

This section presents a brief programming description for implementing the alternate classification subroutine, here called ACS.

Each entry into the ACS will result in the attempted classification of one designated target.

The various items of input data required by ACS are shown in Table 5-1. It is assumed that there are up to 20 types of targets, here denoted by the subscript I, and that the simulated operator will select either one of these or noise, (I = 21) to designate his response on the basis of the probability functions described. The operator selected for the job of classifying the designated target is predetermined and is passed to ACS by the MAIN program as the variable M which is used to identify the proper operator speed/proficiency value F(M) The target to be identified, IT, is similarly passed and allows the selection of the appropriate value of the visibility indicator V(IT) used in the prior classification and scan/detect subroutines. The similarly matrix (V_{ij}), described above, is here denoted VE(I,J) where I and J are the indices for stimulus and response. The input parameter, ALTS, serves to indicate the number of target types (plus 1) selected in the current simulation run and has a minimum value of 4 and a maximum value of 21. This maximum value serves as the index limit for I and J throughout the subroutine, consisting of 20 targets and response types plus noise. The response bias vector containing ALTS elements is identified as RB(J), J=1,...,ALTS.

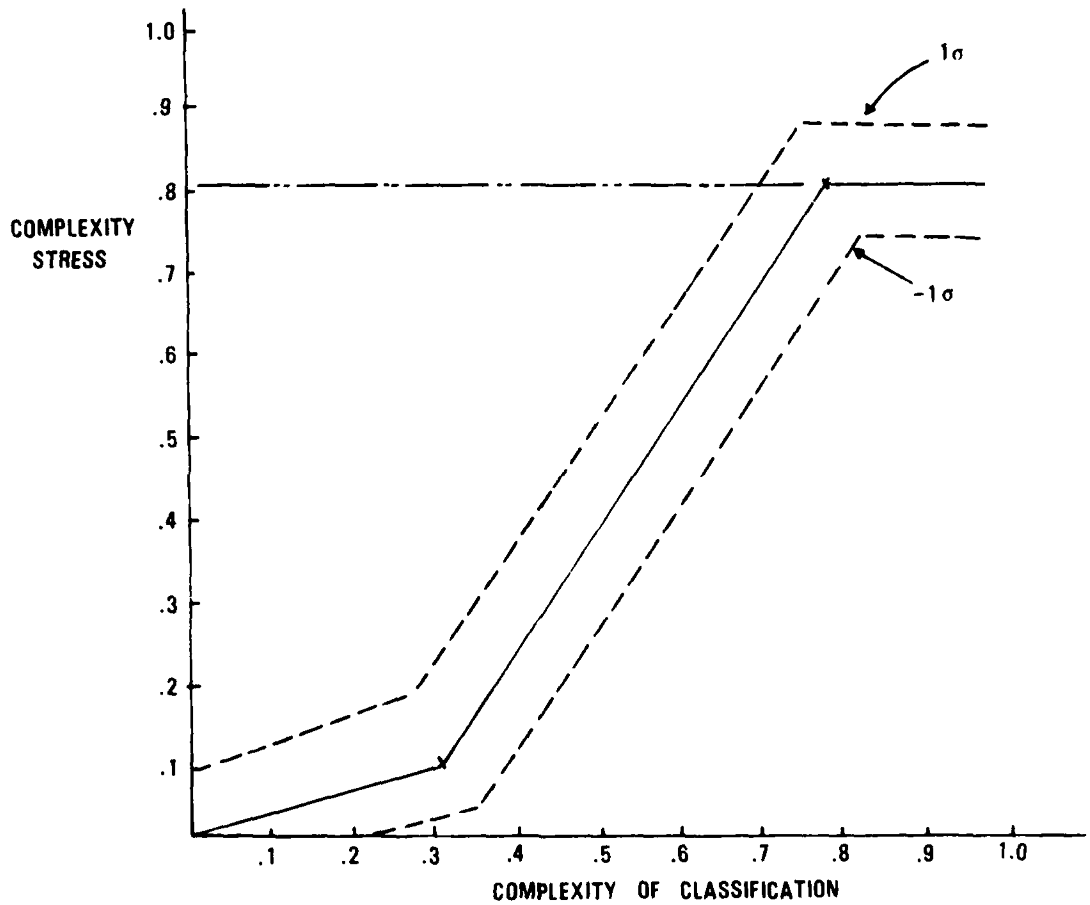


Figure 5-2. Relationship Between Classification Complexity and Stress.

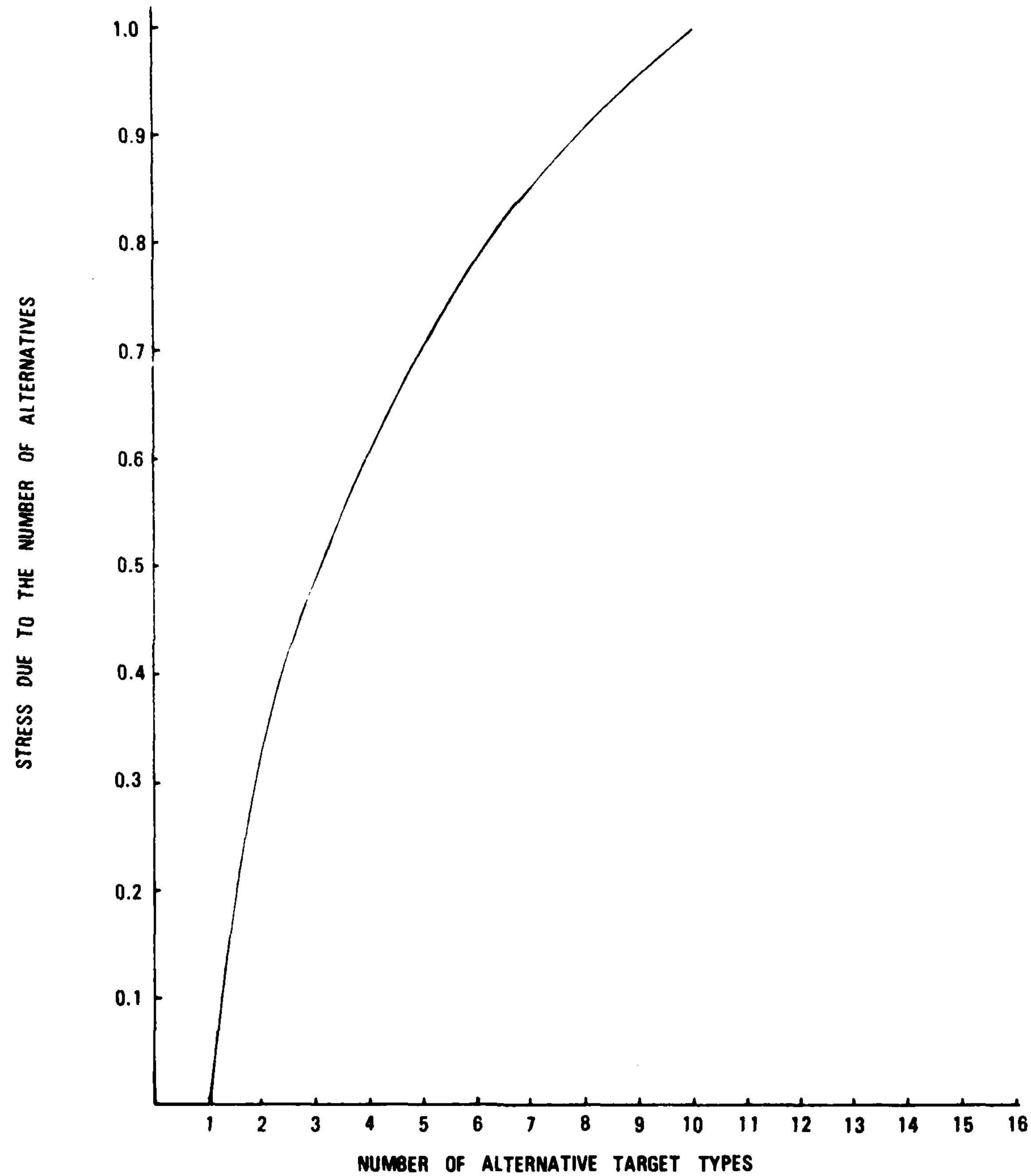


Figure 5-3. Relationship Between Number of Alternatives and Stress.

Figure 5-5 presents the detailed logic flow for ACS corresponding to the global flow diagram in Figure 4-1. The numbering scheme in Figure 5-5 follows that of Figure 5-1 to indicate subordinate processes in Figure 5-5. Each major element of the computation sequence contains a brief plain-sense description of the function/purpose performed by that box as well as a programming oriented description of the procedure in terms of the various data items. All variables used in these calculations which are not listed in Table 5-1 (inputs) are shown either in Table 5-2 (other variables) or in Table 5-3 (ACS outputs).

TABLE 5-1

ALTERNATE CLASSIFICATION SUBROUTINE INPUTS

1.	Operator number for the operator assigned to classify	M
2.	Operator speed (proficiency) 1:nominal;≤:faster;≥1:slower	F(M)
3.	Number of the target to be classified	IT
4.	Correct number for this target type (answer)	ITC
5.	Visibility indicator for target number IT. 0 — not visible now 1 — visible first time 2 — visible, not first time	V(IT)
6.	Similarity matrix containing values for the similarity of appearance between each target type and all others and with noise	VE(I,J)
7.	Response bias vector 0(no bias) to 1(high bias)	RB(J)
8.	Maximum number of target types plus 1 = number of alternatives plus 1 21≤ALTS≥4	ALTS
9.	Detection/classification status 1 — (not applicable to this subroutine) 2 — target detected 3 — classified successfully 4 — passed to other operator 5 — active 6 — failed to detect 7 — classified unsuccessfully	DCS(IT)

TABLE 5-2

OTHER ACS SUBROUTINE DATA ITEMS

	Values
Index for stimulus target types, 1..., ITAR	I
Index for response target types, 1,..., ITAR	J
Simulated target type selected by operator	ISTAR
Stress due to complexity	CSTR
Stress due to the number of alternatives	ASTR
Pseudo random number, equiprobable in 0 to 1 range	RY
Random deviate, a number selected from a normal distribution average = 0, sigma = 1	RD
Random factor used in classification time calculation	RF
Total operator classification stress	STR
Response probability matrix, C_{ij}, per Townsends formula	RPM(I,J)
Column vector used to cumulate RPM column entries	COL(I)
Largest value in RPM(I,J) matrix	RPMMAX
Complexity of classification	CPLX
Percent time increase due to stress used in classification time calculation	PTI

TABLE 5-3

ACS SUBROUTINE OUTPUTS

1.	Performance time of operator classification task	CTIME
2.	Results of classification S — successful U — unsuccessful	RCC
3.	Detection/classification status 3 — classified successfully 7 — classified unsuccessfully	DCS(IT)
4.	Problem flag 1 — visibility indicator not set 2 — target not previously detected	PF

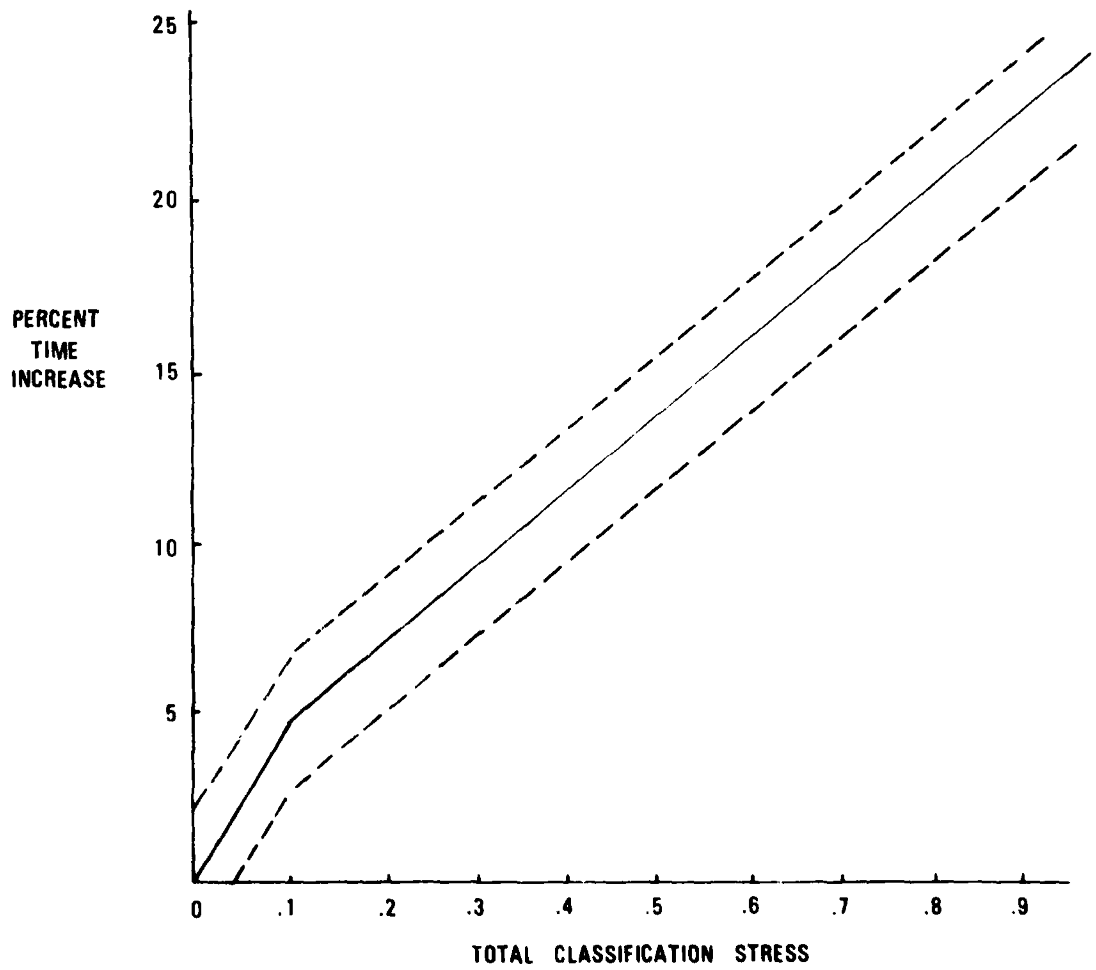


Figure 5-4. Relationship Between Classification Stress and Percentage Increase in Classification Time.

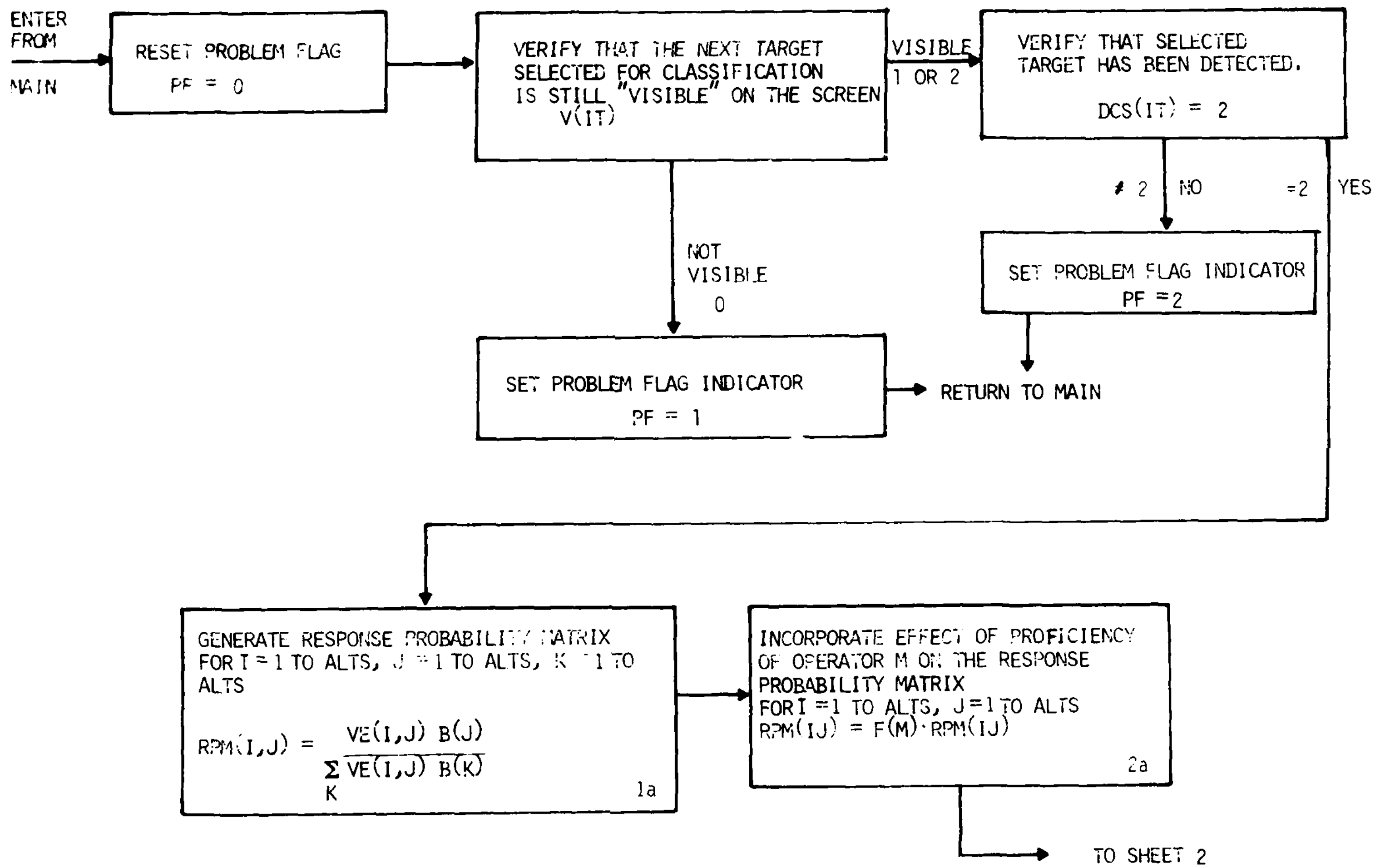


FIGURE 5-5 SHEET 1 DETAILED SUBROUTINE FLOW LOGIC.

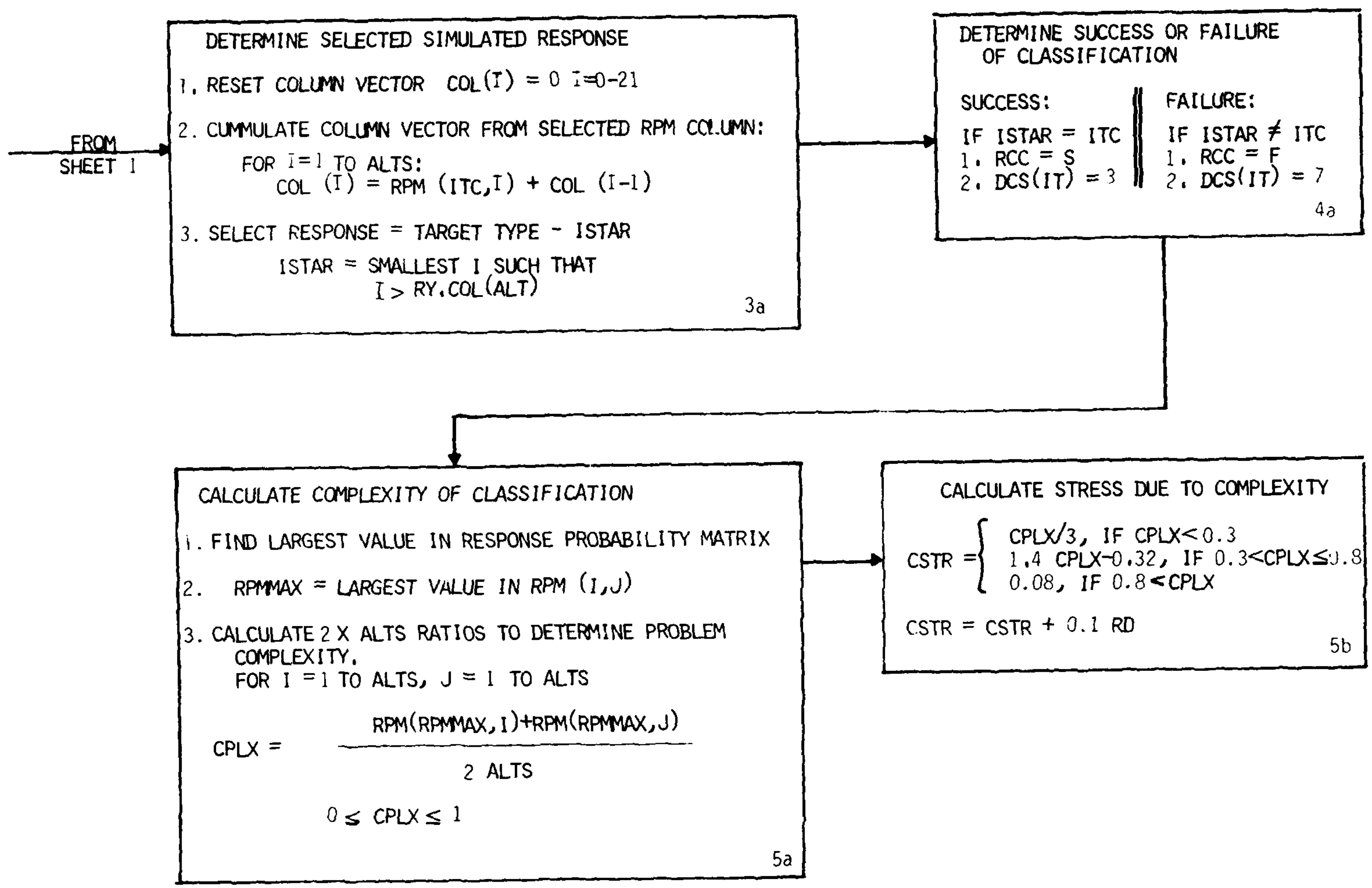


FIGURE 5-5. SHEET 2 DETAILED SUBROUTINE FLOW LOGIC.

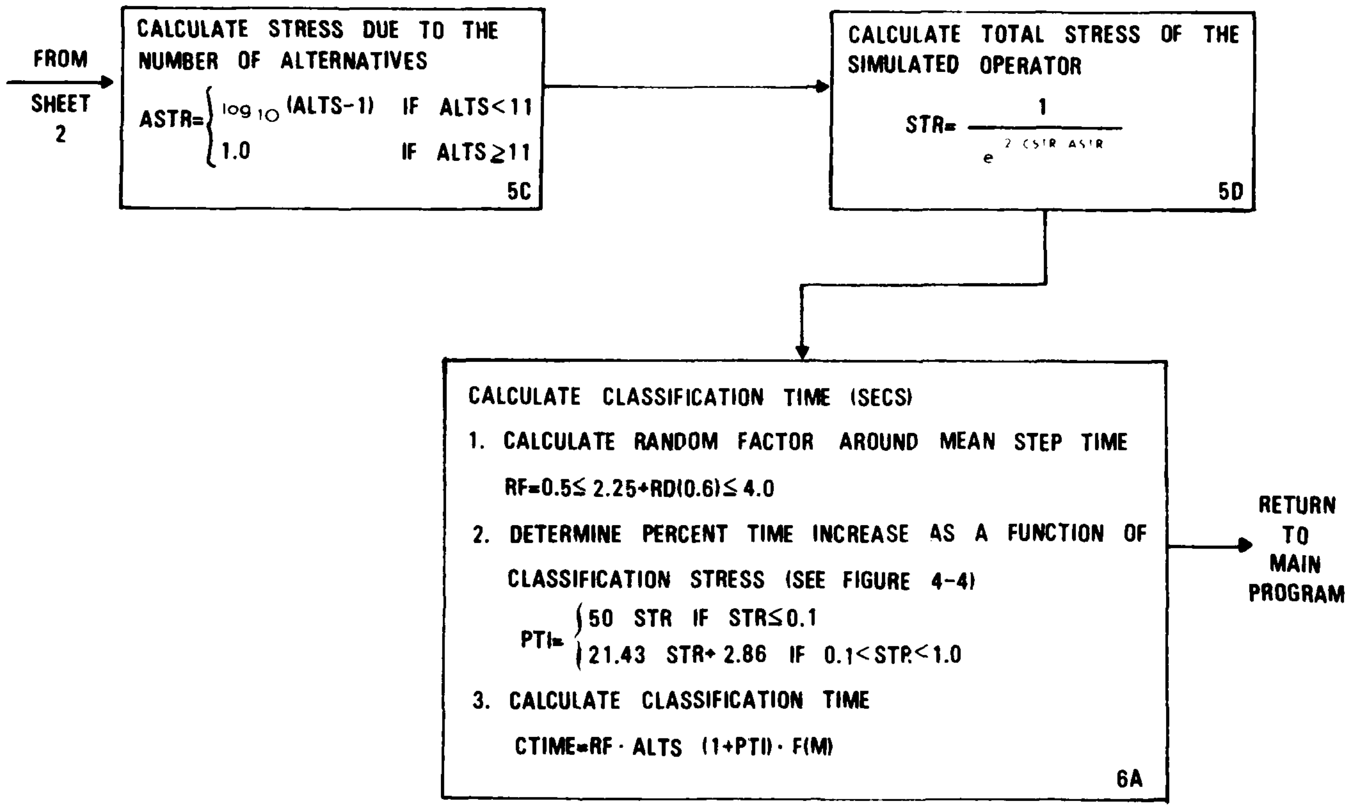


FIGURE 5-5 SHEET 3 DETAILED SUBROUTINE FLOW LOGIC.

The subroutine operations begin with the reset of the problem flag, PF, and the conduct of the two checks utilized in the prior classification subroutine. The first tests to verify that the specified target number, IT, is currently in view by the operator. The second test verifies that the detection sequence has, in fact, been performed on this target. If either error condition exists, PF is set and the control is returned to the MAIN program.

Normally, however, the processing will proceed to calculation of the response probability matrix, RPM(IJ), using Townsend's formula, followed by the modification of each of the elements in RPM(IJ) using the selected operator's speed/proficiency value F(M) as a multiplier as shown in boxes 1A and 2A of Figure 5-5.

In box 3A, a column vector COL(I) is defined containing for each element the sum of all elements in prior rows. The last (ALTS) value of this vector will be unity, neglecting round off truncation errors. Multiplying this last element by RY, a pseudo random number in the 0 to 1 range, will enable simulation of the target selection process in accordance with the probabilities represented by the elements in COL(I). The target selected, called ISTAR, is the smallest I which exceeds RY·COL(ALT).

If this target selected is, in fact, the one designated by parameter input to be the correct one, ITC, then appropriate indicators are set in box 4A to record success in the classification process. Otherwise a failure is similarly indicated.

Next, in boxes 5A, 5B, 5C, and 5D, the calculations involved with complexity and stress are implemented. A series of ratios, 2·ALTS in number, are determined using the elements in the row and column of the response probability matrix which has the largest element. The average of these ratios is called complexity, CPLX, and is used as shown in Figure 5-2 to determine the stress due to complexity, CSTR. The stress due to the number of alternatives, ASTR, is determined per Figure 5-3 and combined with CSTR in box 5D to obtain a total value for stress of the classification operator.

The last box, 6A, of Figure 5-5 shows the implementation of the classification time calculation as a function of:

(1) a random deviate, RY, used to generate a factor RF, limited to lie between 0.5 and 4.0 seconds. RF represents the unit classification time.

(2) the number of alternatives, ALTS, which represents a measure of the simulated operator's choice space.

(3) a factor, PTI, which can influence an increase in classification time as a result of the total stress (CSTR) previously calculated. No effect of this factor will be observed if the AN/UPD-X operator is in a no-stress state. Per Figure 5-4, an increase of over 24% is possible for exceptionally high values of stress (STR=1).

(4) the operator speed/proficiency value, scaled so as to be a multiplier. Fast operators will have parameter values F(M) less than unity thus resulting in a linear reduction in classification time compared to the nominal operator for whom F(M)=1.

Calculation of the classification time, CTIME, in seconds then completes the ACS processing and control is returned to the MAIN program, leaving in common storage the resultant output data shown in Table 5-3.

SECTION VI
DECISION MODULE

This section presents the computer module for simulating decision tasks within the AN/UPD-X system. The module's logic follows from Simon and Newell's problem solving theory, (Simon & Newell, 1971; Newell & Simon, 1972), but expands on that conceptualization by considering task complexity, decision utility, operator ability, stress, and Bayesian concepts. Here the AN/UPD-X operator to be simulated is the problem solver to whom the Simon & Newell theory is applied. In short, the Simon-Newell theory describes the problem solver as stepping, node by node, through the problem space until a solution or final decision is reached. The node stepping represents the decision process where each step involves a datum collection, analysis, and evaluation and the problem space represents the size and structure of the decision task. This stepping process of problem solving has been observed and simulated in at least three types of problem tasks: (1) chess playing, (b) cryptarithmetic, and (c) discovering proofs in logic (Newell & Simon, 1972). Similarly, Laming (1968) described and presented evidence for and described a "random walk model" of the decision process.

THE DECISION PROCESS

Decision making concerns the choice between two or more alternatives; it involves such processes as observation, thought, and response on the part of the AN/UPD-X operator.

In making a (rational) decision, a person: (a) searches for and collects information through observation, (b) analyzes the information to compare alternative action avenues, and (c) chooses an alternative based on some criterion or goal of the decision task. The decision process, in short, involves information processing, and fits the familiar S-O-R paradigm: the stimulus is the information observed, the decision maker analyzes and evaluates the information, and the response is the choice among the alternative responses available to the decision maker.

Paterson (1972) more formally described decision making as follows:

> "Decision-making implies a decision process, a sequence of four stages, stimulation which becomes *Information*, assessment of the information to present *Conclusions* or alternatives for action, selection of an alternative which becomes a commitment to action and so a *Decision* proper, and, finally, the stage of *Execution* requiring decision on how to carry out the commitment (Paterson, 1972, p. 7)."

The decision subroutine directly involves Paterson's first three steps—information, conclusions, and decision; the fourth step, execution, is more related to the event simulator.

The decision process has been previously modeled in a number of different ways. One type of decision model has simulated decision making as a constrained random—although not haphazard—process. Such a process is involved in Laming's random walk model (Laming, 1968) and was used to simulate decision tasks in an early version of the Siegel-Wolf model (Siegel & Wolf, 1969, p. 28).

A second type of decision subroutine represents a more rational process; it involves a choice among alternatives based on the expected utility or value of the alternatives. In the optimal situation, on the basis of data collection and analysis, the decision maker selects the response alternative which possesses the greatest expected utility or payoff. Most mathematical theories of decision making are based on the expected utility principle (e.g., Thurstone, 1927; Coombs, 1958; Luce, 1959). This maximum utility decision process was incorporated into a later version of the Siegel-Wolf digital simulation model, (Siegel, Wolf, Fischl, Miehle, & Chubb, 1971).

A third type of decision subroutine might be involved if the decision task involves probabilities which are modified as information is progressively obtained. Faced with a decision, the decision maker collects, analyzes and evaluates information, and attempts to solve the problem by selecting the correct response alternative on the basis of probability based information. Simon and Newell's (1971) problem solving representation, and Bayesian approaches (e.g., Edwards, 1954, 1961) incorporate probability concepts.

The present decision simulation is primarily concerned with a probability oriented decision process. The module is based on Simon and Newell's (1971) problem solving approach and Bayesian processes which are suitably modified by complexity, utility, stress, and individual competency considerations. The end result of the simulation is an indication of: (1) the correctness of the decision, and (2) the time required for decision making. The incorporation of decision complexity, ability, and stress variables is justified by the general concept that performance is dependent on characteristics of: (a) the task itself, (b) the human performer, and (c) the task environment.

SIMON AND NEWELL'S PROBLEM SOLVING MODEL

Based on over two decades of research, Simon and Newell developed a theory which attempts to describe and explain the cognitive processes in problem solving. Their description of the problem solving processes portrays the problem solver as an information processor making choices among alternative routes in a heuristically governed search for the problem's solution. Simon and Newell (1971) described the human problem solver as a:

> ...serial information processor with limited short-term memory [which] uses the information extractable from the structure of the space [perceived problem task]...to evaluate the nodes [observed information] it reaches and the operators [data analysis] that might be applied...The evaluations are used to select [partial decision] a node and an operator for the next step of the search. Operators are usually applied to the current node [state of knowledge] but if progress is not being made, the solver may return to a prior node that has been retained in memory (page 153).
> (parenthetical material added)

THE DECISION TASK

Utilizing the Simon and Newell stepping representation of decision making, the present decision subroutine was based on up to five decision alternatives, (one and only one of which is correct) and six nodes (for a total of 11 states). As represented in Figure 6-1, the decision task may be viewed as a hexagonal structure.

The structure may be initially entered at any node. Direct entry to a solution state is not permitted. From any node, 11 choices are available: stepping to one of the other five nodes, remaining at the node, or stepping to a solution state. Stepping to a solution state completes the stepping process.

Two output measures are produced by the decision subroutine: decision time and decision success. Decision time is a function of task complexity, stress, and the number of steps to reach a solution, where each step equals a unit of time. The minimum time situation occurs when reaching a decision state takes only two steps (start to node and node to solution state). Although the decision time maximum is theoretically indeterminate because it is possible for the stepping process to continue ad infinitum, a maximum number of steps has been incorporated for programmatic practicality.

Given a correct solution, decision success is determined by matching the solution reached (via the stepping process) to a given (subroutine input) correct solution.

Within the step process, the step probability values, initially supplied as subroutine input, are affected by: (1) operator ability, (2) utility, and (3) a Bayesian process.

OVERVIEW OF SIMULATION PROCESS

An overview of the simulation sequence is presented as Figure 6-2. As shown in Figure 6-2, the AN/UPD-X decision task simulation starts with a number of input data items. After input and operator selection,

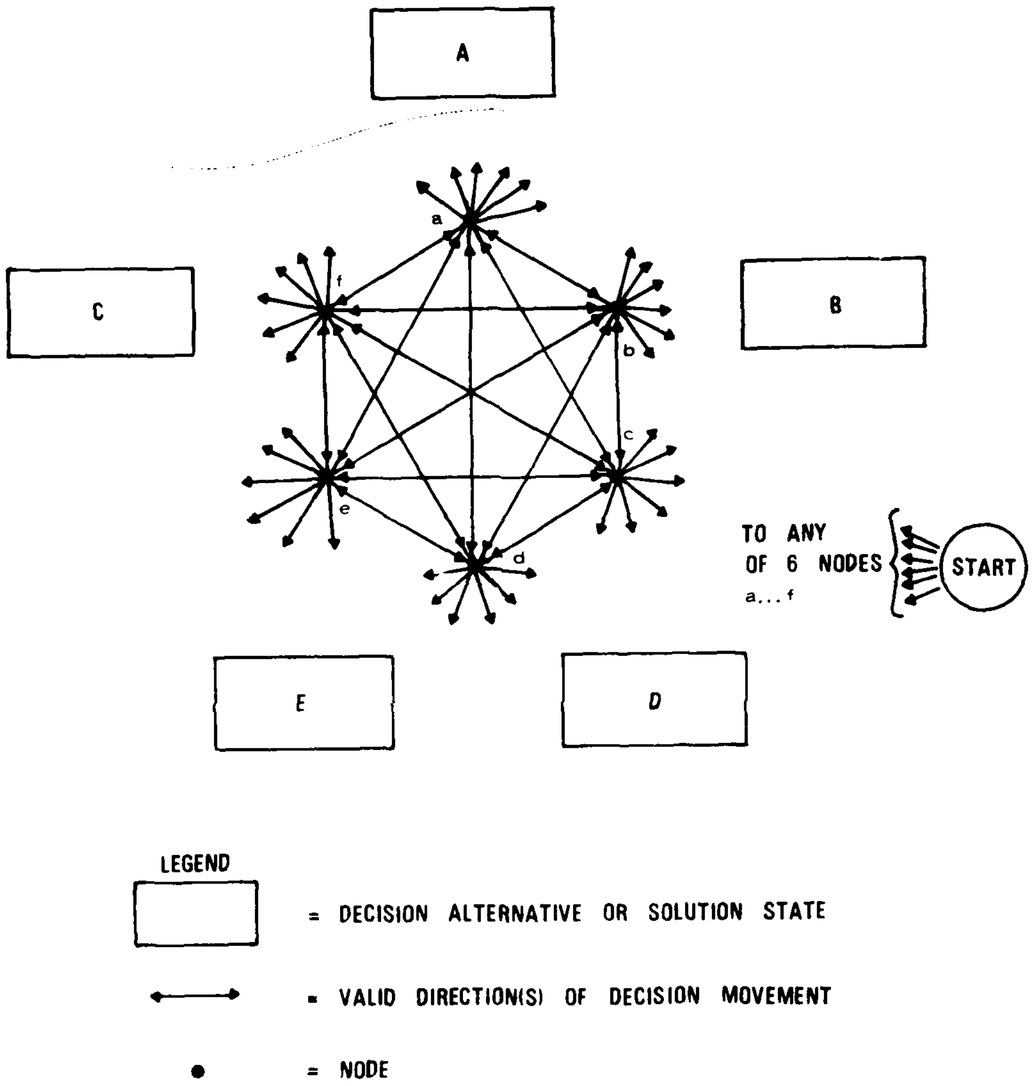


FIGURE 6-1. PARTIAL REPRESENTATION OF A FIVE-SOLUTION, SIX-NODE PROBLEM REPRESENTATION.

the step probabilities are first adjusted for operator ability and utility. Next (following resets), the decision implement step is taken. If a decision state is reached, the correctness of the decision is determined and the simulation proceeds to the decision time calculation sequence (boxes 9 through 12, Figure 6-2). If no decision state is entered, the input probability matrix is altered by a Bayesian process and a probability ratio required in the later complexity calculation is obtained. Then, performance of the next step is simulated, and the decision-no-decision check is again made. This process continues until a decision state is entered, or until the number of steps has reached the prespecified limit. The details of the decision making subroutine are described below, and in the section on the programmatic aspects of the subroutine.

DECISION SUBROUTINE INPUT REQUIREMENTS

The input requirements (box 1, Figure 6-1) for the decision subroutine are:

1. node to node movement probability matrix, standstill probability, and node to decision probability
2. identification of the correct decision alternative
3. goal importance matrix
4. matrix of effects of each course of action on goals
5. entry node probabilities
6. operator ability level (speed/proficiency)
7. maximum number of decision steps permitted
8. identification of operators involved in this decision.

An example of the composition of the node to node, node to decision, and standstill probability matrix is presented as Exhibit I. The Exhibit I matrix is not symmetrical and the column sum must equal one. In the absence of other information, the correct decision alternative may be arbitrarily selected by the analyst prior to data input.

The goal importance matrix and the matrix representing the effects of each course of action on the goals are discussed in a subsequent section.

Equiprobable entry node probabilities may be employed in the absence of other information.

DECISION MAKER SELECTION

If there is more than one person involved in the simulation, the decision maker to be simulated is selected (box 2, Figure 6-2). If this information is not specified by the MAIN program, the AN/UPD-X operator in the simulated group having the highest speed/proficiency factor is selected as the decision maker. In the case of a tie in ability, the choice is made by a random process.

ADJUSTMENT FOR OPERATOR ABILITY

The input step probabilities are then adjusted for ability of the AN/UPD-X operator (box 4, Figure 6-2).

Operator speed/proficiency is a multiplicative factor and is treated here in the same manner as in the other subroutines. Average ability is 1.00 and such a value has no affect on the input probability matrix. Decision maker speed/proficiency values less than 1.00 (greater speed/proficiency) cause an increase in the input probability sets for moving from any node towards the correct solution along with a corresponding decrease in the probability of moving toward the wrong nodes. If the decision maker's speed/proficiency, however, exceeds 1.0, then the probabilities of making the correct decision are decreased and the other probabilities are increased accordingly. Accordingly, in box 3 of Figure 6-2, the input proba-

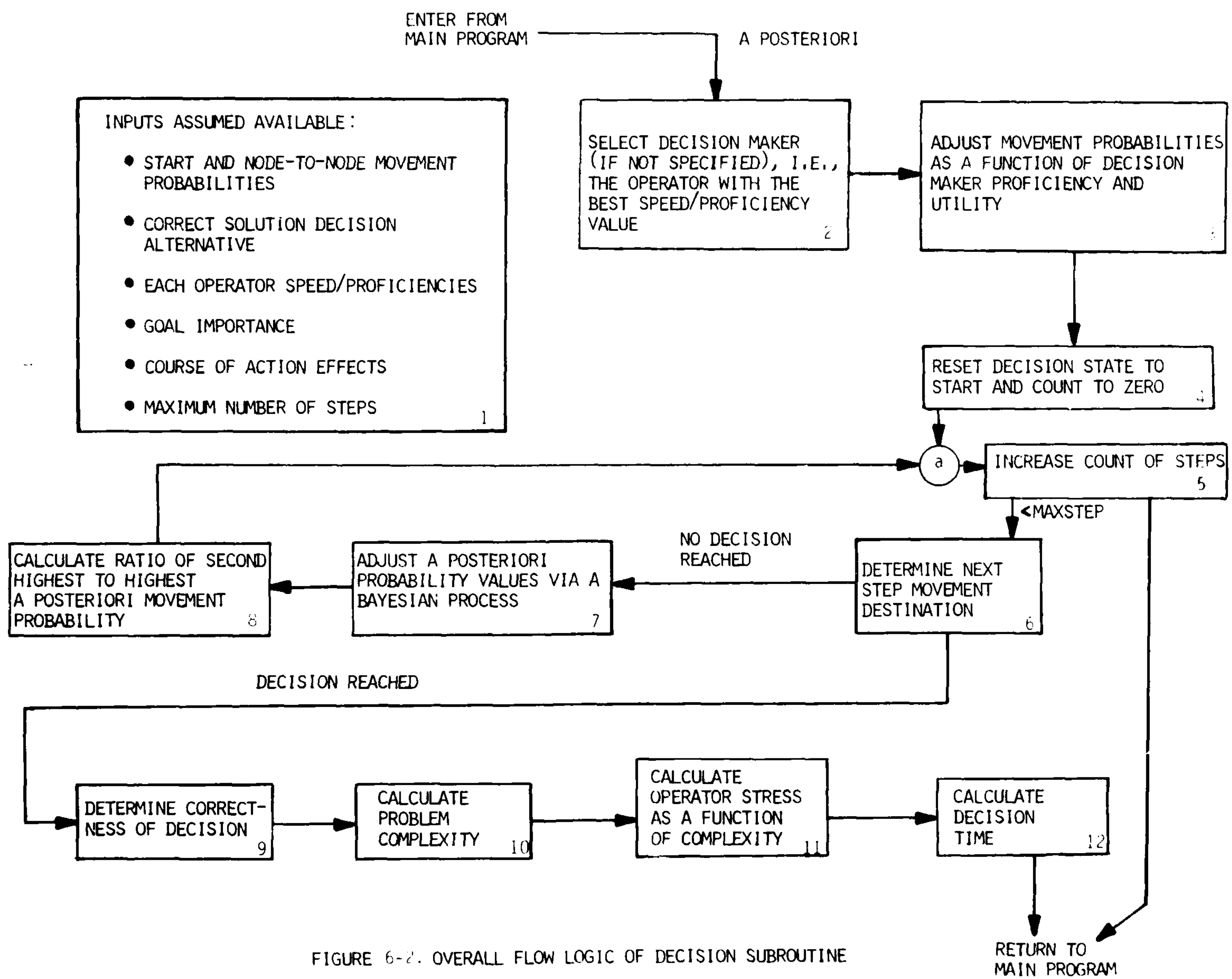


FIGURE 6-2. OVERALL FLOW LOGIC OF DECISION SUBROUTINE

bility matrix and the starting state probabilities are first adjusted for operator ability. Note that, at the conclusion of this adjustment, the column sums are still equal to one.

ADJUSTMENT FOR UTILITY

Having revised the input probability matrix for operator ability, the adjusted matrix is then revised for the utility of the various decision alternatives. The best solution is not necessarily the solution with the highest probability. The utility adjustment is performed on the basis of two sets of input data: (1) importance of the decision on up to any three preselected mission goals, and (2) the effects of each course of action on the goals (there are five of these). Sample data for these are shown in Table 6-1.

The utility calculation is performed as the result of a set of matrix multiplications. Consider three goals and five alternatives. The importance of the goals may be represented by a goal importance vector such as that which is shown in Table 1(a) while the effects of each course of action on the goals may be represented by an effects matrix such as that shown in Table 1(b).

The utility of each decision state may then calculated as the vector product of the goal importance vector and the vector for each alternative. For example, the calculation for the utility of the third alternative is:

$$V_3 = [.4 \quad .5 \quad .1] \begin{bmatrix} .3 \\ .3 \\ .4 \end{bmatrix}$$

$$= .31 \quad \text{as shown in } \textit{Table 6-1(c)}$$

Once the utility of each decision state is calculated in this way, the lowest decision alternative is assigned a weight of one; other decision alternatives are assigned weights in accordance with the ratio of their utility to the utility of the lowest alternative. The assigned input probabilities of moving to a decision alternative as previously modified are then altered by these weights. This is a direct multiplicative process.

$$PS_{ij} = K_i \times PS_{ij}$$

where:

PS_{ij} = the weighted stepping probability of the ith node

K_i = the utility of the ith solution state

PS_{ij} = the modified starting probability of the ith solution state of ijth node.

The weighted stepping and entering probabilities are proportionally adjusted to allow the sum of the probabilities to equal one. To this end, each weighted probability is multiplied by the sum of the original unweighted probabilities for the weighted states. Then, this product is divided by the sum of the weighted probabilities. This reads:

$$AUPS_{ij} = (PS_{ij} \times \Sigma WPS_{ij}) / \quad \Sigma PS_{ij} = WPROB$$

where:

$AUPS_{ij}$ = altered utility weighted starting probability of the ith solution state or ijth node.

ΣWPS_{ij} = sum of unweighted starting probabilities for weighted states.

ΣPS_{ij} = sum of weighted starting probabilities.

EXHIBIT I

EXAMPLE OF INPUT MATRIX

Probability of Movement From

		a	*b*	*c*	*d*	*e*	*f*	*Start*
	a	0.1*	.	.	etc.	.	.	.
	b	.	.	.	etc.	.	.	.
	c	etc.	.	.	etc.	.	.	.
	d	.	.	.	etc.	.	.	0.3*
	e	.	.	.	etc.	.	.	.
	f	.	.	.	etc.	.	.	.
To								
	A	0.05*	.	.	etc.	.	.	0
	B	.	.	.	etc.	0.3*	.	0
	C	etc.	.	.	etc.	.	.	0
	D	.	.	.	etc.	.	.	0
	E	.	.	.	etc.	.	.	0
	SUM	1.0	1.0	1.0	1.0	1.0	1.0	1.0

*Subsequent text explains these entries

The utility weighting is not applied to the starting state probabilities because it is assumed that there can be no utility until after the first step. Conceptually, no information is available to the AN/UPD-X decision maker until after the initial step is completed.

STEP PROCESS

Within the decision subroutine, Monte Carlo methods are employed to complete the stepping process (box 6, Figure 6-2). In Exhibit I, the lower case letters (a, b, c, d, etc.) represent a node. Initially entering node d, for example, possesses a probability of .30. The standstill probability at node a is .10. All nodes have an associated standstill probability. The probability of moving from node a to solution state A is .05 while the probability of moving from node e to solution state B is .30.

TABLE 6-1

SAMPLE GOAL AND COURSE OF ACTION DATA

Relative Goal Importance, GI(J)

	J	*1*	*2*	*3*	*Sum*	
Sample values:		0.4	0.5	0.1	1.0	
Sample goals:		accuracy	speed	operational capability	—	(a)

Course of Action Effects, CA(J,IDA)

J	*IDA:*	*A*	*B*	*C*	*D*	*E*	*Sum*	
1		.2	.1	.3	.3	.1	1.0	
2		.0	.3	.3	.2	.2	1.0	(b)
3		.1	.2	.4	.0	.3	1.0	
U	IDA	.09	.21	.32	.22	.17	1.0	(c)

For example, the stepping process may run:

a-f-c-d-e-f-a-A

This decision process example took nine steps or time units where the starting state is the first step. The entered solution state A is "right" or "wrong" as indicated by input. Other decision simulations may proceed 1, 50, 100 or some larger number of steps. As a result, a limit parameter is used to prevent too long a sequence.

To determine which step is actually taken, a stochastic process is employed as shown in the section on program implementation.

BAYESIAN PROCESSOR

Next the decision is compared with the input correct decision to determine decision correctness.

If the decision step results in entry into a node, as opposed to a decision state, the set of weighted stepping probabilities is adjusted on the basis of a Bayesian logic. Bayes' theorem represents a method for converting *a priori* (probability prior to obtaining information, evidence, or experience) probability information to *a posteriori* (probability after obtaining information, evidence, or experience) probabilities on the basis of intervening information.

The following illustration of Bayes' rule is taken from Fishburn (1964). Suppose Smith opposes Jones in an election with three voters. If x denotes the number of votes received by Smith (x = 0, 1, 2, 3), 3-x is the number of votes Jones receives. Before the election, based on his knowledge of Jones and the voters, Smith arrives at the following *a priori* probabilities for x.

$$\text{For Smith: } \begin{aligned} P(x = 0) &= 1/25, \\ P(x = 1) &= 8/25, \\ P(x = 2) &= 14/25, \\ P(x = 3) &= 2/25. \end{aligned}$$

Suppose there is one ballot to be opened, and that ballot is for Jones. Let J_1 be the event in which the first ballot is for Jones. The conditional probabilities of J_1, given x_1 are:

$$\text{For Smith: } \begin{aligned} P(J_1 \mid x = 0) &= 1, \\ P(J_1 \mid x = 1) &= 2/3, \\ P(J_1 \mid x = 2) &= 1/3, \\ P(J_1 \mid x = 3) &= 0. \end{aligned}$$

Smith can now compute the *a posteriori* probabilities (P(x|J1) using the following relationships.

$$P(x|J_1)P(J_1) = P(J_1|x)P(x),$$

$$P(J_1) = \sum_x P(J_1|x)P(x) = 1/25 + 2/3(8/25) + 1/3(14/25) + 0(2/25) = 33/75,$$

to yield

$$\begin{aligned} P(x = 0|J_1) &= 3/33, \\ P(x = 1|J_1) &= 16/33, \\ P(x = 2|J_1) &= 14/33, \\ P(x = 3|J_1) &= 0. \end{aligned}$$

After each step of the decision process in the decision subroutine, the current node to node movement matrix is updated on the basis of Bayes' rule (box 7, Figure 6-2). After the first step, the input matrix constitutes the *a priori* information. After subsequent steps, the updated input matrix of the prior step is employed as the *a priori* matrix. Accordingly, the *a priori* matrix is successively updated to an *a posteriori* matrix and the *a posteriori* matrix for one step becomes the *a priori* matrix for the next step.

In order to apply Bayes' rule after each step, one must know how much information is gained at each step of the decision process, i.e., the conditional probability after each step. To this end, before the Bayesian processing, each step entry (excluding initial entry probabilities) in the input matrix (Exhibit I) is stochastically updated at the end of each step. The updating is performed by selecting a random number between 0 and .5 from a rectangular distribution. Then, each entry in the input matrix is processed in accordance with the Bayes' logic described above. We note again that, in this application, the input matrix represent the *a priori* information and the stochastically selected number represents the conditional probability.

As stated above, each *a posteriori* matrix becomes the *a priori* matrix after the subsequent step.

DECISION TIME

The prior calculation provides output about the number of steps to the decision and the correctness of the decision (boxes 5 and 9, Figure 6-2). The decision time determination is based on a separate logic. Specifically, decision time is based on the stress on the simulated AN/UPD-X operator making the decision, the number of steps taken, and the problem complexity.

RELATIONSHIP BETWEEN STRESS AND PROBLEM COMPLEXITY

The stress on the simulated operator is assumed to be a function of the complexity (difficulty) of the decision. An easy problem is one on which the *a posteriori* probability set for one alternate is considerably larger than the *a posteriori* probability for any other alternate. In such a problem situation there is little confusion about which way to go. The problem is said to be easy. A difficult problem is one on which equiprobable alternatives exist.

After each step, the ratio of the second highest to the highest *a posteriori* value is determined and stored. At the conclusion of the decision simulation, these values are averaged to yield an average "complexity" value which will fall between zero and one. Figure 6-3 presents the assumed relationship between stress and complexity. As complexity increases, stress is assumed to increase only slowly until complexity reaches a value of 0.3. At this point, the problem's difficulty is assumed to become sufficient to cause an increase in the rate of stress development. When the average complexity reaches the 0.8 complexity level, the rate of stress buildup decelerates.

To allow for human and situational variability, the stress value employed is selected stochastically from a distribution in which the average stress value is employed as the mean and the one standard deviation limits are those shown in Figure 6-3.

AFFECT OF STRESS ON DECISION TIME

Each step of the decision process is assumed to take some time. The step time basis is drawn from a review of a set of studies into decision time. The studies reviewed and their results are summarized in Table 6-2. The table includes a wide variety of studies which ranged from discrimination reaction time to more complex decision making. From Table 6-2, it appears that decision speed in laboratory studies seldom was less than .50 seconds and was seldom more than 4.0 seconds. In the decision subroutine, the number of steps to a solution is multiplied by a random number drawn from a normal distribution between .50 and 4.0 with a mean of 2.25 (center of range) and a standard deviation of 1.2 (about one third of the range).

Accordingly, the number of steps to a solution is multiplied by the basic step time to yield an initial estimate of decision time. This initial estimate is then treated by stress to derive the final decision time. In this manner, stress may be considered to be an intervening variable which affects decision time on the basis of task complexity. The assumed relationship between stress and decision time is presented in Figure 6-4. Again, a stochastic effect is included.

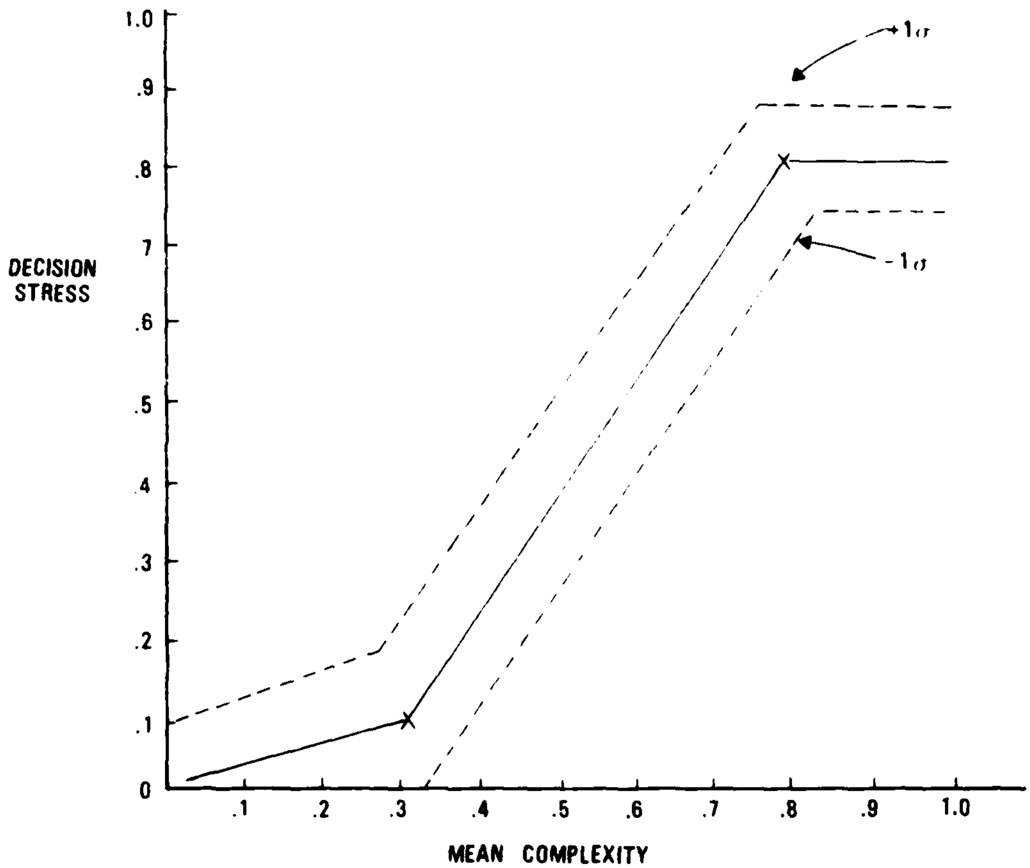


Figure 6-3. Relationship Between Problem Complexity and Stress.

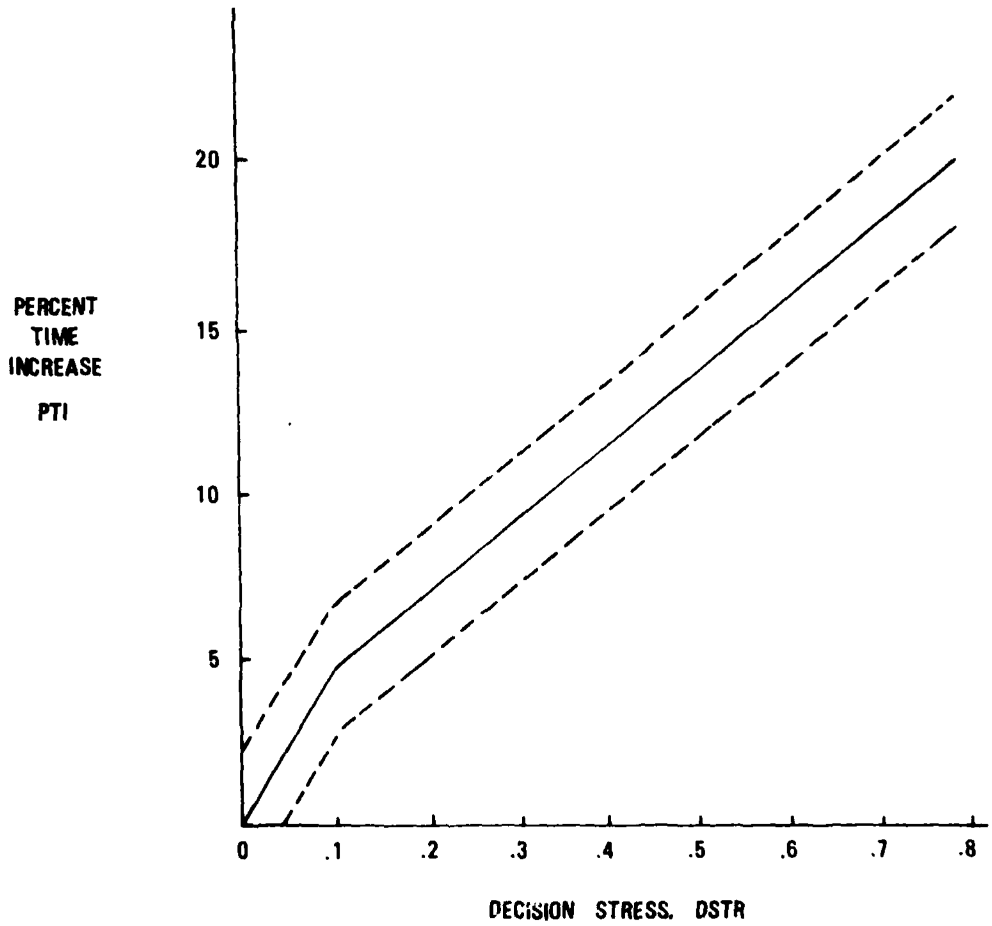


Figure 6-4. Relationship Between Decision Stress and Percentage Increase in Decision Time.

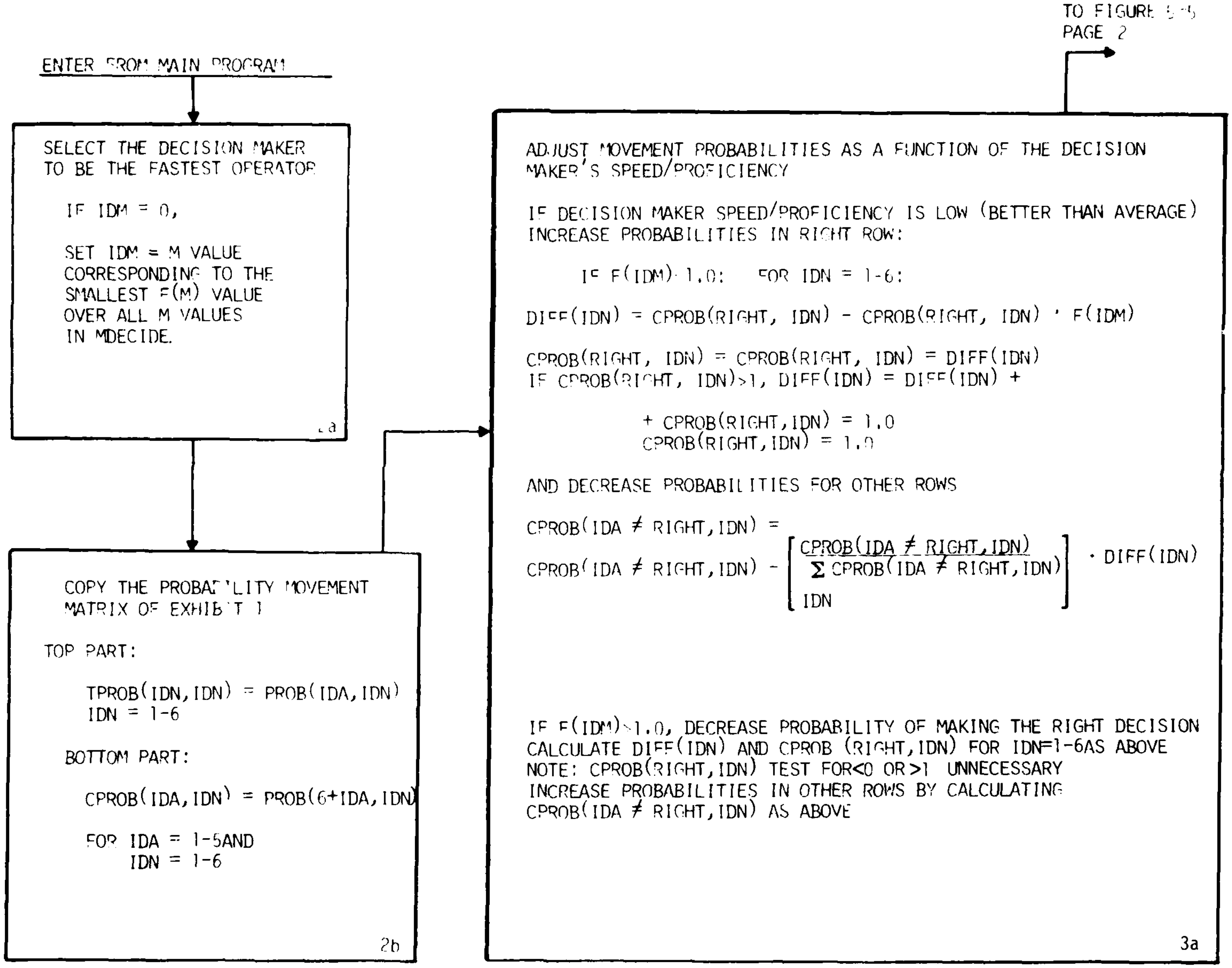


FIGURE 6-5. DETAILED LOGIC FOR THE DECISION MODULE

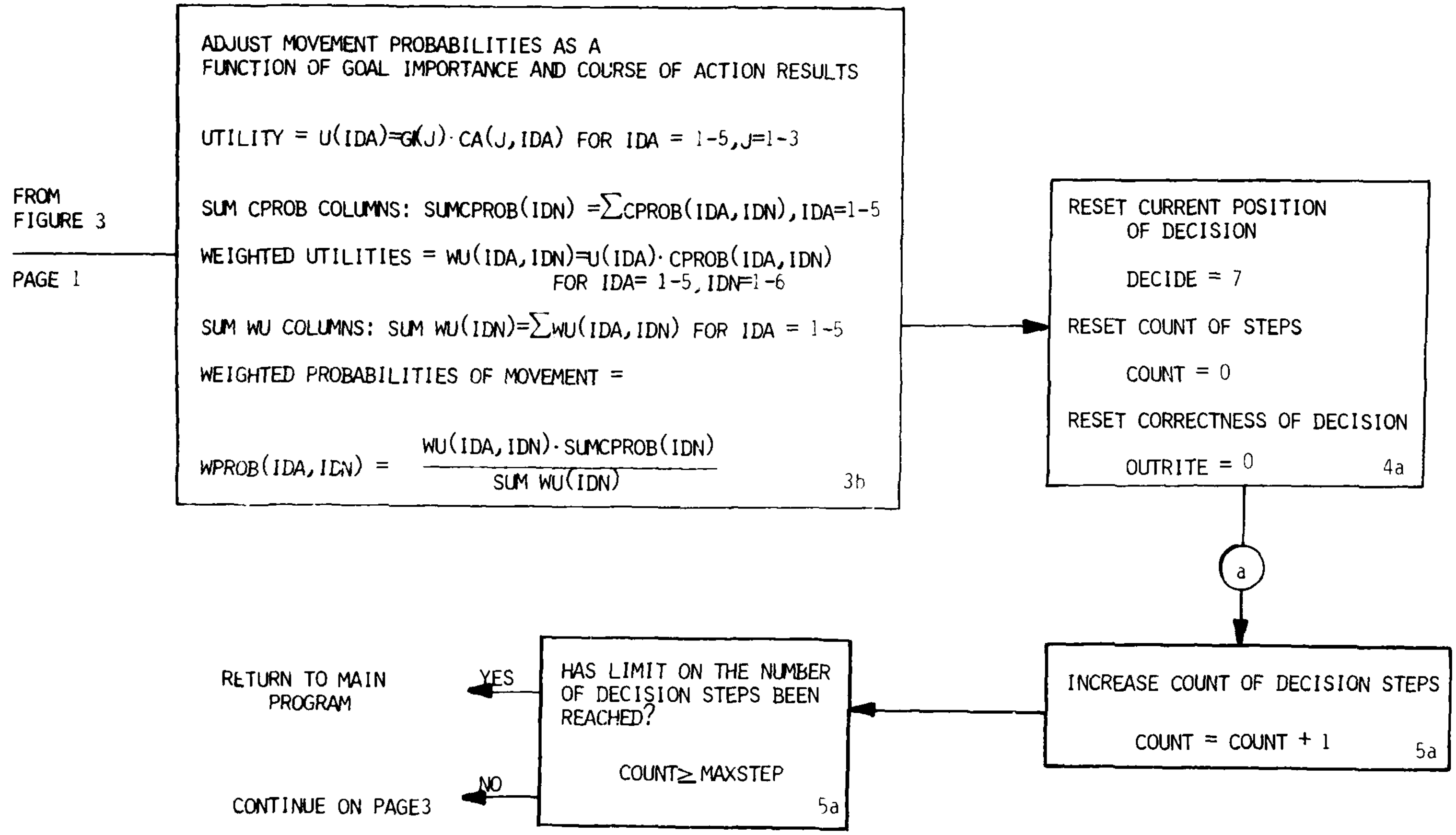


FIGURE 6-5. DETAILED LOGIC FOR THE DECISION MODULE (CONT.) PAGE 2

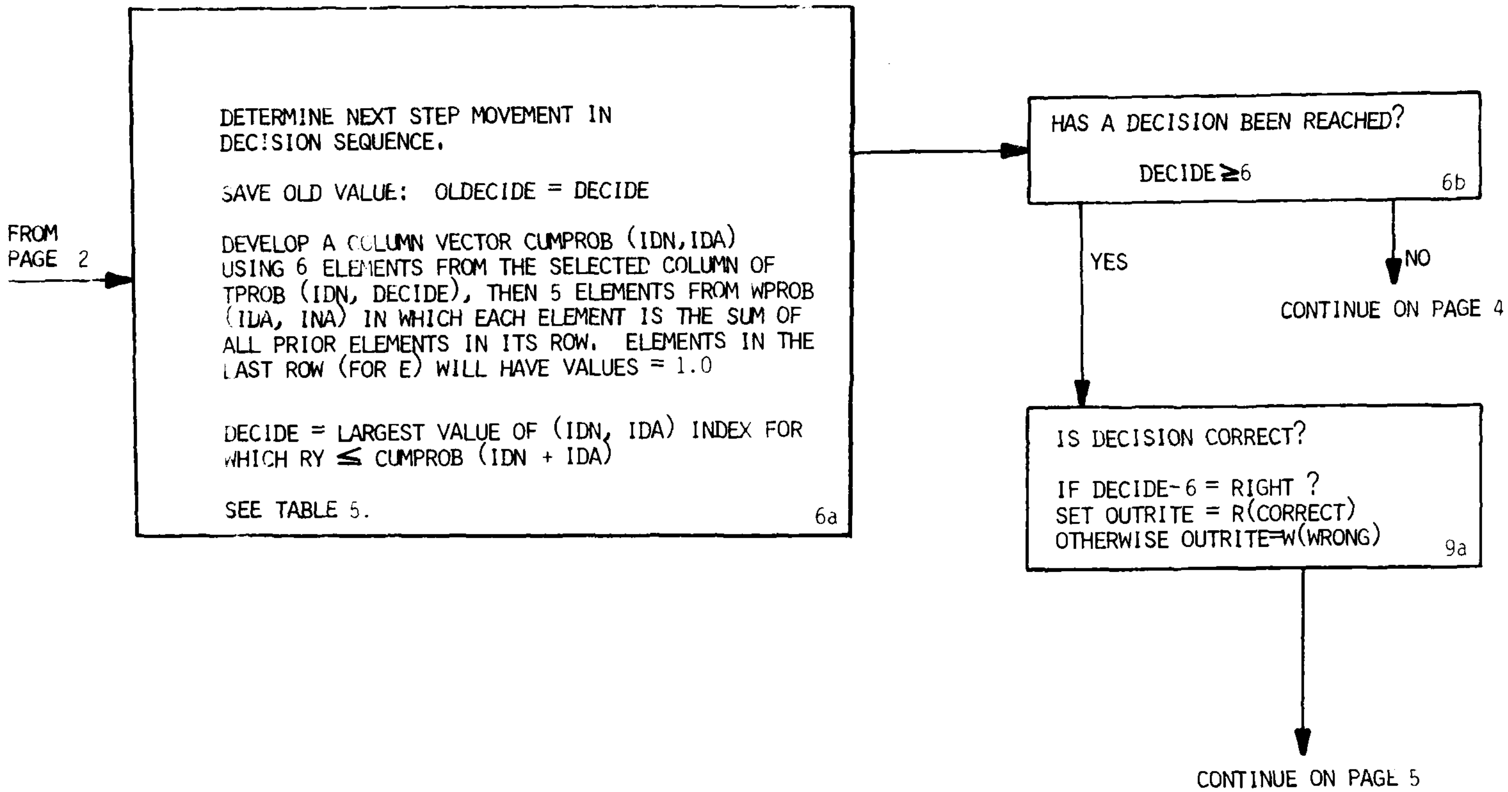


FIGURE 6-5. DETAILED LOGIC FOR THE DECISION MODULE(CONT.), PAGE 3

ENTER FROM PAGE 3

CALCULATE CONDITIONAL PROBABILITIES FOR THE BAYESIAN PROCESS

1. DEVELOP A PRELIMINARY CONDITIONAL PROBABILITY VECTOR, $P[J_1/X]$,

   COND(IDN) =(RY 0.5) USING A DIFFERENT RY FOR EACH ELEMENT, IDN = 1-6

2. CALCULATE THE VECTOR PRODUCT $P(J_1)$ =PJONE

   $$\text{PJONE} = \sum_{\text{IDN}} [\text{COND (IDN)} \cdot \text{TPROB (DECIDE,IDN)}] \quad \text{FOR IDN} = 1\text{-}6$$

3. CALCULATE A POSTERIORI PROBABILITIES, $P(X_1/J_1)$, FOR THE ROW IDN = DECIDE.

   $$\text{TTPROB (DECIDE,IDN)} = \frac{\text{COND (IDN)} \cdot \text{TPROB (DECIDE, IDN)}}{\text{PJONE}} \quad \text{FOR IDN} = 1\text{-}6$$

4. ADJUST MATRIX ELEMENTS SO ROW TOTALS WILL REMAIN EQUAL TO 1 FOR ROWS WITH IDN ≠ DECIDE

$$\text{PDIFF (IDN)} = \text{TTPROB (DECIDE,IDN)} - \text{TPROB (DECIDE,IDN)} \quad \text{FOR IDN} = 1\text{-}6$$

$$\text{TPROB(IDN} \neq \text{DECIDE,IDN)} = \text{TTPROB(IDN,IDN)} + \left[\frac{\text{TTPROB (IDN,IDN)}}{\sum_{\text{IDN}} \text{TPROB(IDN,IDN)}}\right] \text{PDIFF (IDN)}$$

$$\text{TPROB(DECIDE,IDN)} = \text{TTPROB(DECIDE,IDN)} \quad \text{FOR IDN} = 1\text{-}6$$

7a

CALCULATE RATIO OF SECOND HIGHEST TO HIGHEST A POSTERIORI MOVEMENT PROBABILITY

$$\text{SUM (IDN)} = \sum_{\text{IDN}} [\text{TPROB (IDN,IDN)}]$$

SUM ACROSS FOR IDN = 1-6

$$\text{RATIO(COUNT)} = \frac{\text{SECOND LARGEST SUM (IDN)}}{\text{LARGEST SUM(IDN)}}$$

8a

a

TO PAGE 2

FIGURE 6-5. DETAILED LOGIC FOR THE DECISION MODULE (CONT.), PAGE 4

AD-A097 622 DAYTON UNIV OHIO F/G 9/2

COMPUTER SIMULATION OF HUMAN PERFORMANCE IN ELECTRONIC PROCESSE--ETC(U)

JAN 81 A I SIEGEL, R F BACHERT F33615-77-C-0520

UNCLASSIFIED AFAMRL-TR-79-117 NL

2 OF 2

AD A 097622

END

DATE FILMED

5-81

DTIC

DA
097

FROM PAGE 3

CALCULATE PROBLEM COMPLEXITY

$$COMPLEX = \frac{\sum_{I=1}^{COUNT} RATIO\ (I)}{COUNT} \leq 1$$

10a

CALCULATE DECISION STRESS.

$$DSTR = \begin{cases} COMPLEX/3 & IF\ COMPLEX \leq 0.3 \\ 1.4(COMPLEX)-0.32 & IF\ 0.3<COMPLEX\leq 0.8 \\ 0.8 & IF\ 0.8<COMPLEX\leq 1.0 \end{cases}$$

$$DSTR = DSTR + 0.1(RD)$$

$$0 \leq DSTR \leq 0.8$$

11a

CALCULATE DECISION TIME

1. DETERMINE PERCENT TIME INCREASE AS A FUNCTION OF DECISION STRESS:

$$PTI = 50\ DSTR\ IF\ DSTR \leq 0.1$$
$$= 21.43\ DSTR + 2.86\ IF\ 0.1 < DSTR \leq 0.8$$

2. CALCULATE RANDOM FACTOR AROUND MEAN STEP TIME:

$$RFST\ \ 0.5 \leq 2.25+RD(1,2) \leq 4.0$$

3. CALCULATE

$$DTIME = COUNT \left(1 + \frac{PTI}{100}\right) RFST$$

12a

RETURN TO MAIN PROGRAM

FIGURE 6-5. DETAILED LOGIC FOR THE DECISION MODULE (CONT.), PAGE 5

TABLE 6-2

SUMMARY OF DECISION SPEED STUDIES REVIEWED

Author	*Source*	*Task*	*Results (Decision Time)*
Seibel, R.	J. Exp. Psychol, 1963, *66*, 215-219	Discrimination reaction time for a 1,023 alternative task	Time varied between .35 and 1.3 sec
Pitz, G.F. & Geller, E.S.	J. Exp. Psychol., 1970, *83*, 400-405.	Sequential information presented	Time varied between .56 and 2.50 sec. in accordance with a "response repetition" effect
Okada, R.	J. Exp. Psychol., 1971 *90*, 27-32.	Reaction time in a continuous recognition memory task	Time varied between [illegible] and .80 sec
Fischler, I. & Juola, J.F.	J. Exp. Psychol., 1971, *91*, 54-58	Recognition of words in memory	Time varied between .6[illegible] and .85 sec.
Keele, S.W.	J. Exp. Psychol., 1970, *85*, 157-162.	Decision time when number of response categories and dimensionality of stimuli are varied	Time varied between .5[illegible] and .80 sec.
Lovelace, E.A., & Snodgrass, R.D.	J. Exp. Psychol., 1971, *88*, 258-264.	Differentiate between correctly ordered letters—memory scan	In four separate experiments, time varied between 1.[illegible] and 4.0 sec.
Corballis, M.C., & Miller, A.	J. Exp. Psychol., 1973, *98*, 379-386.	Scan memory and decide on appropriateness of letter stimulus	Time varied between .8 and and 1.6 sec
Kennedy, A.	J. Exp. Psychol., 1973, *98*, 432-434.	Theme *recognition in prose—memory scan* and extrapolation	Time varied between .9 and and 1.5 seconds with significant cue by response type interactions
Juola, J.F., Taylor, G.A., & Young, M.E.	J. Exp. Psychol., 1974, *102*, 1108-1115.	Recognition and encoding of words and pictures	Except for one type of trial which was higher, time varied between .6 and .9 sec
Howard, D.V.	*Human Learning and Memory*, 1976, *2*, 566-576.	Memory search and decision with varying instructions	Decision time varied between 1.4 and 1.8 sec.
Koppell, S.	Human Learning and Memory, 1977, *3*, 445-457.	Memory search and comparison	Time varied between .5 and 2.7 sec.

TABLE 6-3

PARAMETERS AND INPUTS FOR DECISION SUBROUTINE

1.	Nodal transition probability table (see Exhibit I)	PROB(IDN+IDA, IDN+1)
2.	Correct decision alternative number (1-5)	RIGHT
3.	Relative importance of 3 goals, $\Sigma GI(J)=1$, $J=1,2,3$	GI(J)
4.	Course of action effects	CA(J,IDA)
5.	Operator speed proficiency $0.5 \leq F(M) \leq 1.9$	F(M)
	Value — *operator speed proficiency* 1 — nominal 1 — faster higher than average 1 — slower lower than average	
6.	Decision maker, an operator number (integer), optionally available from Main Program	IDM
7.	Maximum number of decision steps permitted	MAXSTEP
8.	Operator numbers for those operators participating in the decision task	MDECIDE(M)

TABLE 6-4

OTHER DATA ITEMS

Item	*Data Name*
Decision time (seconds)	DTIME
Decision complexity	COMPLEX
Decision alternative number A thru E: (1 through 5)	IDA
Decision nodes values a, b, c, d, e, f (1 through 6)	IDN
Operator number	M
Index for goal importance values	J
Course of action index	A
Utility of each decision alternative	U(IDA)
Lower portion of move probability matrix (to decision points)	CPROB(IDA, IDN)
Top portion of move probability matrix, working copy	TPROB(IDN,IDN)
Move probabilities weighted by goal and course of action effects	WPROB(INA,IDN)
Weighted utility probability matrix	WU(IDA, IDN)
Decision state or current position of decision a=1, b=2...f=6, start=7, A=8...E=12	DECIDE
Pseudo random number, equiprobable in the range 0-1	RY

Pseudo random number, normal distribution, Mean O, SD 1	RD
Count for the number of decision steps	COUNT
Correctness of decision taken — O none, R-right, W-wrong	OUTRITE
Sum of weighted move probabilities by decision alternative	SUM(IDA)
Ratio of second largest to largest sum of weighted probabilities	RATIO(COUNT)
Decision stress	DSTRESS
Temporary value for prior value of decision state	OLDECIDE
Conditional probability vector used in Bayesian process	COND(IDA)
Intermediate variable in Bayesian process	PJONE
Temporary matrix for TPROB in Bayesian process	TTPRB(IDN,IDN)
Percentage time increase due to stress	PTI
Random factor around mean step time	RFST

TABLE 6-5

ADJUSTMENT OF TRANSITION PROBABILITIES

(a) CPROB(IDA, INA) =

IDA \ IDN	a	b	c	d	e	f
A	.05	.02	.03	.05	.08	.0
B	.20	.01	.02	.05	.03	.0
C	.08	.05	.01	.05	.02	.0
D	.10	.05	.05	.01	.01	.0
E	.30	.05	.05	.05	.06	.0
SUM:	.73	.18	.16	.21	.20	.0

= SUM CPROB(IDN)

(b) WU(IDA, IDN) = U(IDA)·CPROB(IDA, IDN)

.0045	.0018	.0027	.0045	.0072	.0
.0420	.0121	.0042	.0105	.0063	.0
.0248	.0155	.0031	.0155	.0062	.0
.0022	.0110	.0110	.0022	.0022	.0
.0510	.0085	.0085	.0085	.0102	0
SUM: .1245	.0495	.0295	.0412	.0321	.0

= SUM WU(IDN)

(c) WPROB(IDA, IDN) =

$$\begin{bmatrix} \dfrac{.0045\text{x}.73}{.1245} \rightarrow .0264 & \ldots \\ .2463 & \\ .1454 & \text{etc.} \\ .0129 & \\ .2990 & \ldots \end{bmatrix}$$

SUM: .73 ...

PROGRAMMATIC ASPECTS OF THE DECISION SUBROUTINE

This selection describes the decision subroutine from the programmer/analyst point of view. Details are shown which relate to the implementation of the various processes previously described in this chapter. The summary flow chart, Figure 6-2, is the basis for the detailed logic of the subroutine. The major result of this section is the elaboration of Figure 6-2 in greater detail as shown in Figure 6-5. A parallel numbering scheme for the boxes is employed in these two figures. In Figure 6-2, logic boxes are numbered 1 through 12; correspondingly, the processes shown in box number n in this figure are detailed in boxes na, nb, etc., in Figure 6-5. Hereafter, in this chapter, all box numbers refer to Figure 6-5 unless otherwise stated.

We consider the situation in which the decision subroutine is entered from the MAIN program whenever a decision task is reached. Up to five alternative decision choices are possible on each decision, but only one is identified as correct. The parameter and other input information passed from MAIN to the decision subroutine are identified in Table 3, which includes FORTRAN names for these data items, (see also Figure 2, box 1). Other data items used in this subroutine are also defined and named in Table 3.

If specified by the MAIN program, the non zero value of IDM determines the operator who is to make the actual decision on a multi-operator task. If IDM is not specified (i.e., IDM=O), the operator who will make the decision is determined by selecting the one whose speed/proficiency, F(M), is lowest over those assigned to this task (see box 2). If all operators in the simulation are always eligible for consideration as the decision maker, all F(M) values should be considered. If a subset is eligible, this subset of operator numbers must also be provided as input (Table 2, Item 8).

Box 2b is included to set up a working copy of the two parts of the input probability matrix in temporary storage. In this way, the 6 x 6 and 5 x 6 portions of the original probability matrix provided as input (Table 2, Item 1), will be used.

The values in this nodal transition probability table are then adjusted in box 3a as a function of the selected decision maker's speed/proficiency value, F(IDM). If this selected F(IDM) value is less than one, signifying a faster or more proficient than average operator, then the value of all transition probabilities in the correct decision row (IDA = RIGHT) are increased as a function of F(IDM). In this case, the value of the probability values in other rows are decreased to make up the difference on a proportional basis (keeping the sum of probabilities for IDA = RIGHT are decreased which simulates slow operators being less likely to make the correct decision. Similarly, in this case, probabilities in other rows are decreased so that the sum of all transitional probabilities will remain 1 for each column of the probability table, Exhibit I. No changes occur in box 3a if F(IDM) equals 1.0.

Box 3b shows the logic for adjusting these resultant transition probabilities CPROB as function of the three goal importance values GI(J),=1, 2, 3, provided as input. Sample data, to illustrate this calculation are shown in Table 4. Given the example goals and values of Table 1(a) and the course of action effects matrix (3 goals by 5 decision alternatives) of Table 1(b), the utility vector U(IDA) of Table 1(c) is calculated as their produce. Sample data for the CPROB probabilities and their column sums (bottom part of Exhibit I only) are in Table 4(a). Using these data, weighted utilities, WU(IDA,IDN) are calculated and summed by column as shown in Table 4(b). These, in turn, are used with the column sums in Table 4(a) to develop modified transition weighted probabilities, WPROB(IDA,IDN), the first column of which is shown Table 4(c), according to the rule:

$$\mathrm{WPROB(IDA,\ IDN)} = \frac{\mathrm{WU(IDA,IDN)} \cdot \mathrm{SUMCPROB(IDN)}}{\mathrm{SUMWU\ (IDN)}}$$

In box 4a of Figure 6-5, several resets are performed prior to enduring the cyclic decision loop. The current value of the decision location, DECIDE, reflecting the node or decision state (i.e., where the process currently rests, (see Figure 6-1) is initially set to seven to represent the starting state. Also the count of the number of decision steps, COUNT, is reset to zero. The output variable specifying the correctness of the final decision (OUTRITE) is reset to 0.

Box 5a starts the cyclic step process with the increase by one of the count of decision transitions. Box 5b contains the test to ensure that the random mark process does not continue indefinitely. If the number of iterations (COUNT) exceeds a preselected limit (MAXSTEP), control is returned to the MAIN program. A value of OUTRITE=O will indicate to MAIN, in this case, that no decision was reached.

Next, in box 6a, the decision state is recalculated, representing a step (usually a movement) within the node selection network. To accomplish this, a new vector of length IDN + IDA is formed using elements from the column of the CPROB and WPROB matrices which represent the current decision state. (An example of this process is shown in Table 6-5.) This is done since the node to node probabilities in the CPROB matrix are unchanged, and the node to decision state values have been modified, their current values being in the WPROB matrix. The column selected is the one representing the current decision state, i.e., the value of *DECIDE*.

The resulting column vector, CUMPROB(IDN + IDA), is formed by accumulating these values. It then has 6 + 5 = 11 elements whose last element should then equal 1. These probabilities reflect the likelihood of stepping to each of the 11 potential next positions. A pseudo random number in the range 0-1 is then selected and compared against the values of CUMPROB to select the movement of the decision state. The new value of DECIDE will be the largest value of the IDN, IDA index (1-11) for which RY $\leq$ CUMPROB (IDN+IDA).

If the new value of DECIDE represents a decision alternative box in Figure 1, i.e., is greater than 6, then a decision has been reached and the processing continues at box 9a and subsequent boxes to conclude the subroutine.

If a decision has not been reached, processing continues in the cyclic loop with box 7a which implements the Bayesian technique. The first step is calculation of a six element vector of conditional probabilities by a random process, COND(IDN). The second step is calculation of the vector product P (J1) $\Sigma P(J1|x) \cdot P(x)$, the sum of six products. The third step is actual calculation of the *a posteriori* probabilities for a single row of the TPROB matrix, i.e., the row decide. This is done using the relationship:

$$P(x|J1) = \frac{P(J1|x)P(x)}{P(J1)}$$

for each of the six elements in the row of a temporary matrix TTPROB. In the fourth and last step of this process, elements of the 6 x 6 probability matrix are adjusted so that there is no change in column sums. To do this, the amount of the differences is saved as PDIFF(IDN) and each column of the TTPROB(IDN, IDN) matrix, in turn, is considered. The sum of elements of all rows in the column except the row IDN = DECIDE is then taken. The new value of each matrix element is changed as a function of the difference and the ratio of that element to the sum of the column elements. In this way a new copy of the TPROB matrix is formed for all other rows.

The last remaining calculation in the decision loop is the development of ratios of *a priori* probabilities required in the calculation of problem complexity.

If the decision has been made in box 6b, processing continues in box 9a with a determination of the validity of the decision. The output indicator OUTRITE is set to R or W to indicate whether the outcome is right or wrong.

Next in box 10a a complexity value of the decision is determined as the average of all the ratios calculated during the decision iterations. Using this value (COMPLEX) and the linear relationships shown in Figure 6-3, the decision stress is calculated as implemented in box 11a. Note that the randomization effect around the nominal stress values is accomplished by adding 0.1 RD to the nominal, where RD is a normal deviate, i.e., randomly selected from a normal distribution with a mean of zero and a standard deviation of one.

Last, decision time is calculated as shown in box 12a. The percentage time increase, PJI, is the function presented in Figure 6-4. The factor RFST is calculated as a sample from a normal distribution with mean = 2.25 to be used as the number of seconds required for each decision movement. Thus the decision time calculated in seconds of time is the result of three factors: the number of steps (COUNT), the time per step RFST, and the influence of decision stress $\left(1+\frac{PTI}{100}\right)$.

Following this calculation, the subroutine is completed and control reverts to the MAIN program.

TABLE 6-6

EXAMPLE CALCULATION OF DECIDE

	Selected Column from TPROB	*Accumulated Column from CUMPROB*	*Example Value of the Pseudo Random Number RY:*	*Selected Value of the Next Decision State:*	*IDN, IDA Index*
a	0.22	0.22	0.293	3 or c	1
b	0.01	0.23		since	2
c	0.15	0.38		.23<.293	3
d	0.08	0.46		.38>.293	4
e	0.10	0.56			5
f	0.03	0.59			6
	Selected Column from WPROB				
A	0.1	0.69			7
B	0.1	0.79			8
C	0.05	0.84			9
D	0.06	0.90			10
E	0.10	1.00			11

SECTION VII
COMMUNICATION

INTRODUCTION

The probability of accurate speech communication between personnel working within the AN UPD-X system is modeled in this chapter with consideration of the message receiver. For purposes of the simulation, it is assumed that persons producing verbal messages do so without error. It is further assumed that any loudspeakers, headphones, and other items of speech transmission hardware are selected and designed for the AN UPD-X system so that the articulation index associated with speech communications approaches 1.0. The accuracy of the listener's reception of speech communication is modeled through application of relevant data concerning human language processing. Specifically, the computation of probability of correct message interpretation is based on research into the correlates of comprehension of textual materials—an area in which there has been considerable recent research.

BACKGROUND

In a series of studies (Siegel & Burkett, 1974; Siegel, Williams, Lapinsky, Warms, Wolf, Groff, & Burkett, 1976; Williams, Siegel, Burkett, & Groff, 1977 a), Applied Psychological Services investigated 14 theoretically based factors related to language comprehension, examined relationships between the factors and comprehension, verified the factors, developed a multiple regression equation which predicts comprehension of text, and performed a study which validated the regression equation.

Normative data were also collected describing the occurrence of the 14 variables in four types of Air Force publication: (1) study guides employed in formal classroom training, (2) manuals and regulations of the type used for field and occasional classroom reference, (3) career development course (CDC) texts (self-study materials used by enlisted personnel to meet a portion of the requirements for upgrading), and (4) technical manuals (publications presenting the specific methods and procedures to be followed on the job and related information). To assemble the normative data, two hundred blocks of text were selected from large samples of each type of publication. In each passage, a carefully supervised analytic team measured the level of each of the 14 variables of interest. At the completion of the analyses, the values were calculated at which the nine deciles occurred for each studied variable. These decile values are employed as indices of message difficulty in the present simulation.

To develop a comprehension equation, 14 passages were selected from U.S. Air Force correspondence course texts concerning technical subjects. Each passage was 600 words in length. Levels of the 14 variables hypothesized to be related to language comprehension were measured in each 100 word portion of each passage. Comprehension of the passages was assessed by application of the cloze technique. The cloze technique, developed by Taylor (1953), is a method for measuring comprehensibility of text. The cloze score is computed as the percentage of deleted words in a passage which is correctly filled in by a subject.

A family of multiple linear regression equations was developed which allow prediction of comprehension (cloze score) as a function of the measured levels of the predictor variables studied. The multiple correlations between cloze score and varying sets of predictor variables ranged from .38 through .61.

A four-variable equation developed by Applied Psychological Services which relates language characteristics to comprehensibility was selected for use in the present work. This equation was found to predict comprehension with moderate adequacy $R=.54$. Of the four variables appearing in the selected equation, two are based on the Structure-of-Intellect taxonomy of mental abilities developed by Guilford and his associates (e.g., 1950, 1954, 1964, 1966, 1967), and two are based on psycholinguistic constructs concerning the manner in which language may be processed. The four are described in greater detail below.

STRUCTURE-OF-INTELLECT VARIABLES

As the result of a research program conducted over many years, Guilford and his associates (e.g., 1950, 1954, 1966, 1967; Hoepfner, Guilford, & Merrifield, 1964) developed a three-factor taxonomy of human mental activity. Based on factor analytic procedures, he described 120 nonoverlapping intellective activities. The three factors isolated by Guilford include: (1) "contents," indicative of the form in which information may be presented, (2) "operations," describing the types of processing applied to the information, and (3) "products," which describe the forms in which the output of the operation may occur. Within contents, four categories exist: figural, symbolic, semantic, and behavioral. Five operations are available: cognition, memory, convergent production, divergent production, and evaluation. The six categories of output include: units, classes, relations, systems, transformation, and implications. Each combination of one content, one operation, and one product represents one unique class of intellective function. The classes, based as they are on combinations of categories within three orthogonal factors, may be represented as a cube composed of 120 cells. Guilford and his colleagues have identified examples of performance and tests for each of a majority of the 120 cells.

Siegel and Bergman (1974) postulated these Guilford abilities to constitute an intervening variable between the surface structure of language (the structure as the message is presented) and the deep structure (the structure after transformation to simplest form is completed). This intervening variable, called "intellective load," has to do with the types and amounts of intellective processes required for converting the coded language into a meaningful message. The components of this intervening variable are based on the taxonomy of mental abilities developed by Guilford and his associates.

Siegel and Bergman (1974) hypothesized that language materials which require a high level of Structure-of-Intellect ability would be less comprehensible than messages requiring the same ability at a lower level. Siegel and Bergman examined the various Guilford categories and selected eight which seemed most relevant to comprehension of language. As the result of an experimental analysis, Siegel and Bergman verified the relationships of levels of the eight selected variables to language comprehension. The two measures which were adopted for the present simulation are Memory for Semantic Units (MMU), and Evaluation of Symbolic Implications (ESI).

MEMORY FOR SEMANTIC UNITS (MMU)

According to Guilford (1967), MMU is closely related to memory for ideas, concepts, or facts. Siegel and Bergman (1974) demonstrated that repetition of facts increases comprehension. The measure of MMU which is used in the multiple regression equation involves the number of different nouns in a message divided by the length of the message in words. Each unique noun is assumed to be associated with a unique idea or concept. Accordingly, the rate of occurrence of new nouns is considered to reflect the number of facts, concepts, etc., which is presented. This measure of MMU was found to be related to message comprehension by Williams et al. (1977 a) and by Siegel et al. (1976).

EVALUATION OF SYMBOLIC IMPLICATIONS (ESI)

Within the Structure-of-Intellect Model, Guilford (1967) stated in regard to the ESI that:

> Since common synonyms for implications are conclusion, inference, or expected consequence or outcome, these are the kinds of mental events that call for evaluation. Are the conclusions sound; are they in all probability correct; do they follow from given information?
>
> ...In a recent analysis (Hoepfner et al., 1964), three tests designed for ESI came out together on a factor. The three ESI tests included Abbreviations, which asks E to say for what word a given abbreviation best stands. An abbreviation implies a word or words for which it stands. Some abbreviation-word conjunctions are more reasonable or apt than others. For example, the abbreviation CRNT might stand for (1) crescent, (2) coronation, or (3) current (p. 200).

Accordingly, the frequency of occurrence of abbreviations in a message may be considered as an indication of the level of mental effort required to understand the message and of the probability of message misinterpretation. Siegel and Bergman (1974) found frequency of abbreviations to be related to message comprehension, and this finding was confirmed by Siegel et al. (1976) and by Williams et al. (1977 a).

PSYCHOLINGUISTIC VARIABLES

Working in parallel with Siegel and Bergman, Lambert and Siegel (1974) sought relationships between language variables suggested by psycholinguistic theory and message comprehension. Two of these variables, Yngve Depth (YD) and Center Embeddedness (CE), appear in the multiple linear regression equation employed in the present simulation module.

YNGVE DEPTH (YD)

A phrase structure hypothesis for describing language behavior was presented by Yngve (1960). According to the hypothesis, sentences are produced, or interpreted, through generation of a "sentence structure tree' in a top-to-bottom, left-to-right direction. At any given time, a listener stores only that portion of the left hand side of the tree necessary to process the words already heard. As the listener works down the tree, he produces both branches of a node, but the words necessary to fill in the right branch of a node are not generally perceived until all words contributing to the left branch have been stored. Accordingly, because of increased memory requirements, sentences whose branching structure is more complex and generally possesses a greater YD value, are held to be more difficult to interpret. Bormuth (1969) found that sentence depth was correlated with the difficulty of a passage. This finding was confirmed by Wang (1970), Lambert and Siegel (1974), and Diegel et al. (1976).

CENTER EMBEDDEDNESS (CE)

It follows from the discussion of YD that the presence of phrases or clauses between the subject and predicate of a sentence should be associated with higher difficulty of comprehension. Such phrases or clauses delay the receipt of the words required to fill in the right branch of the subject-verb split of the sentence.

Schwartz et al. (1970) demonstrated that inclusion of center embedded material decreases comprehensibility. The results of Lambert and Siegel (1974) supported the findings of Schwartz et al. However, Siegel et al. (1976) found that center embedded materials were associated with a higher comprehension level. Siegel et al. indicated that they believed that center embeddedness affects comprehension, but that its measurement is method sensitive.

COMMUNICATION SUCCESS EQUATION

The comprehension equation selected reads:

$$\text{Comprehension score} = .187\text{MMU} + .132\text{ESI} + .156\text{YD} - .0773\text{CE}. \quad \text{(Equation 1).}$$

The comprehension score predicted by this equation is cloze score, as described previously. Cloze score describes the likelihood with which one may correctly determine a word which is missing from text, but not the likelihood of inferring the overall meaning of a message. Accuracy in answering objective questions concerning the content of a message should be closely related to the probability of correct message interpretation. The numerical values of cloze scores, while rather low when compared to scores obtained through more typical comprehension measures (responses to questions of various types), may be converted to comprehension scores. Bormuth (1967) found, for example, that a cloze score of 30% corresponded to a score of 75% on a comprehension test employing objective questions, and that a cloze score of 50% corresponded to an objective score of 90%. In 1968, Bormuth found cloze scores of 44% and 57% to correspond to objective scores of 75% and 90%. In the work of Rankin and Culhane (1969), cloze scores of 41% and 61% were found to correspond to objective test scores of 75% and 90%. From the above data, the relationship between cloze score and correct identification probability was calculated. The equation which expresses the relationship is:

$$p(\text{correct interpretation}) = .622\ (\textit{comprehension score}) + .532.$$

(Equation 2)

And, Equation 1 may be algebraically transformed on the basis of Equation 2 so that it reads:

$$p(\text{correct interpretation}) = .116MMU + .082ESI + .097YD - .048CE + .532.$$

(Equation 3)

SIMULATION OVERVIEW

The processing of the communication module is shown as Figure 7-1. The logic within the blocks of Figure 7-1 is shown in Figure 7-2, a three page detailed flow chart of the functioning of the communication module. The input variables required are defined in Table 7-1. Data items utilized within the module are defined in Table 7-2, and output variables are defined in Table 7-3.

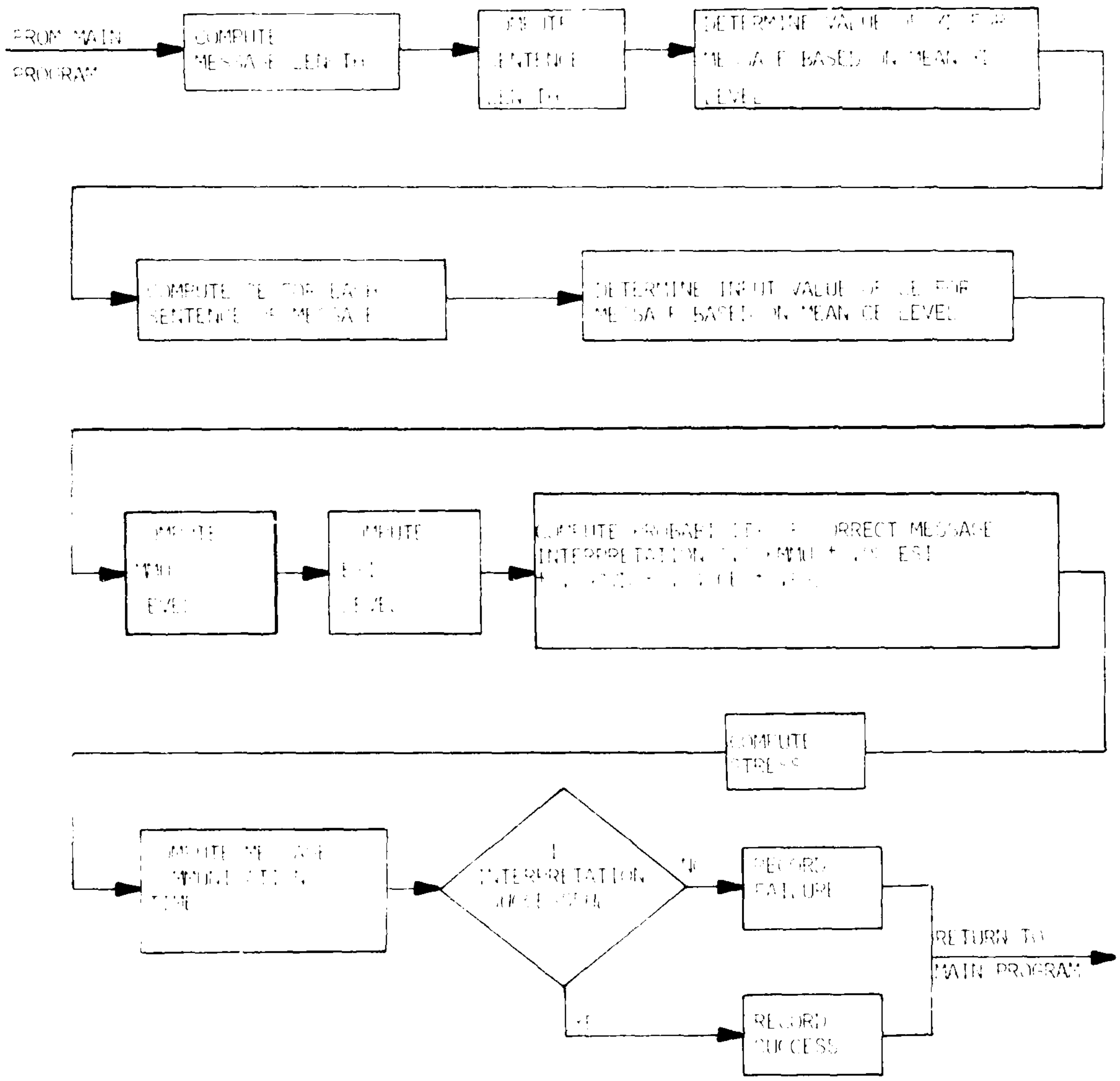


Figure 7-1. Overall Flow Logic for Communication Subroutine.

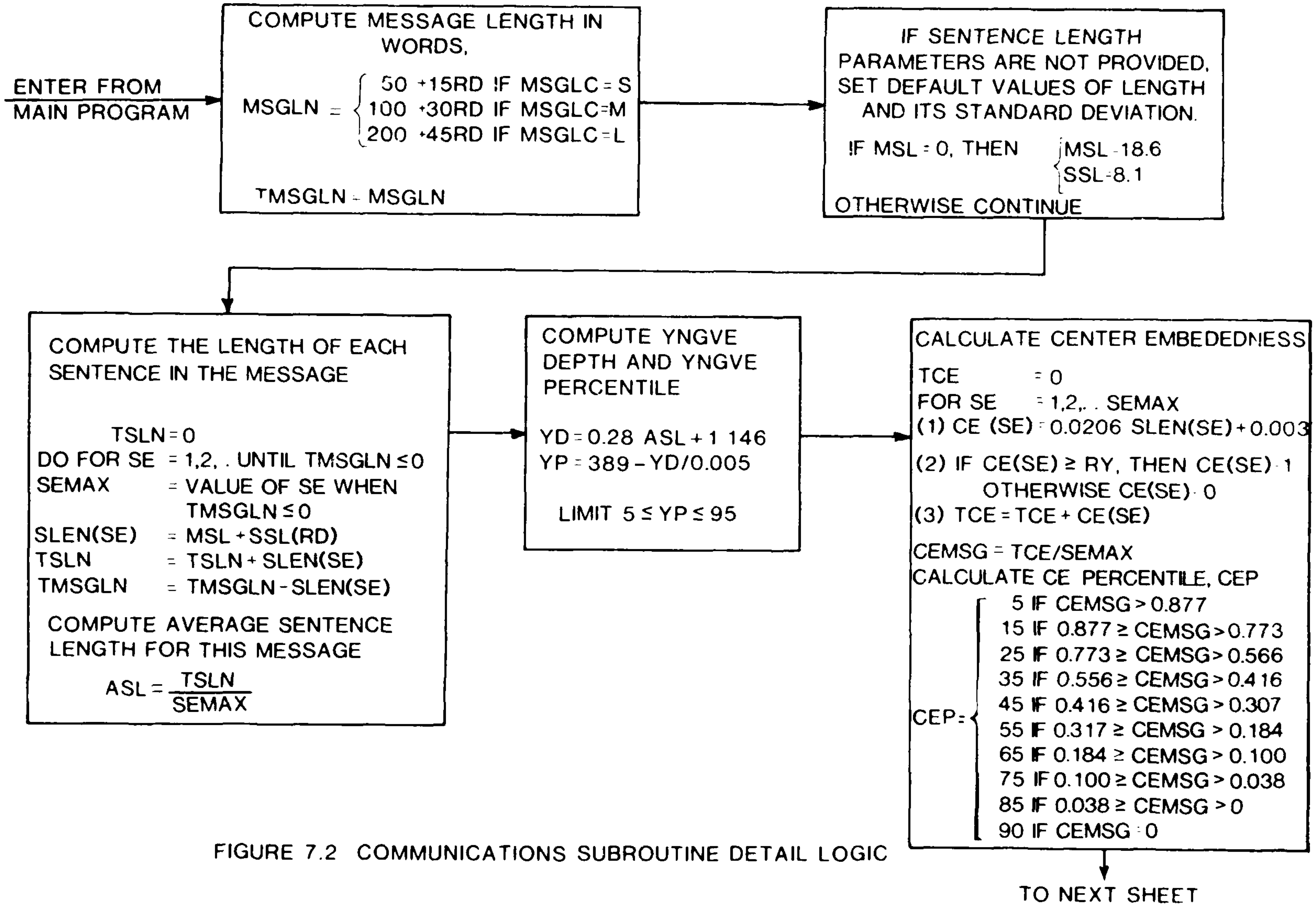


FIGURE 7.2 COMMUNICATIONS SUBROUTINE DETAIL LOGIC

Figure 7-2. Communications Subroutine Detail Logic

FROM SHEET 1

CALCULATE MEMORY FOR SEMANTIC UNITS (MMU)

$$NDN = \frac{TSLN}{9.551}\,(10.321 - LOG_e\ TSLN)$$

$$FNDN = NDN + \left(\frac{NDN}{3}\right) RY$$

$$MMU = 1 - \frac{FNDN}{TSLN}$$

CALCULATE MMU PERCENTILE, MMUP:

$$MMUP = \begin{cases} 5 & \text{IF } MMU < 0.783 \\ 15 & \text{IF } 0.783 \le MMU < 0.802 \\ 25 & \text{IF } 0.802 \le MMU < 0.813 \\ 35 & \text{IF } 0.813 \le MMU < 0.824 \\ 45 & \text{IF } 0.824 \le MMU < 0.832 \\ 55 & \text{IF } 0.832 \le MMU < 0.841 \\ 65 & \text{IF } 0.841 \le MMU < 0.850 \\ 75 & \text{IF } 0.850 \le MMU < 0.861 \\ 85 & \text{IF } 0.861 \le MMU < 0.874 \\ 95 & \text{IF } 0.874 \le MMU \end{cases}$$

CALCULATE EVALUATION OF SYMBOLIC IMPLICATION (ESI)

$$RA = 1.47 + 1.95\ RD$$

$$NA = \frac{(RA)\,(TSLN)}{100} \text{ ROUNDED TO INTEGER}$$

$$ESI = 1 - \frac{NA}{TSLN}$$

CALCULATE ESI PERCENTILE

$$ESIP = \begin{cases} 5 & \text{IF } ESI < 0.943 \\ 15 & \text{IF } 0.943 \le ESI < 0.967 \\ 25 & \text{IF } 0.967 \le ESI < 0.979 \\ 35 & \text{IF } 0.979 \le ESI < 0.989 \\ 45 & \text{IF } 0.989 \le ESI < 0.992 \\ 55 & \text{IF } 0.992 \le ESI < 0.998 \\ 65 & \text{IF } 0.998 \le ESI < 1.0 \\ 80 & \text{IF } ESI = 1.0 \end{cases}$$

TO NEXT SHEET

FIGURE 7-2. COMMUNICATIONS SUBROUTINE DETAIL LOGIC (CONTINUED)

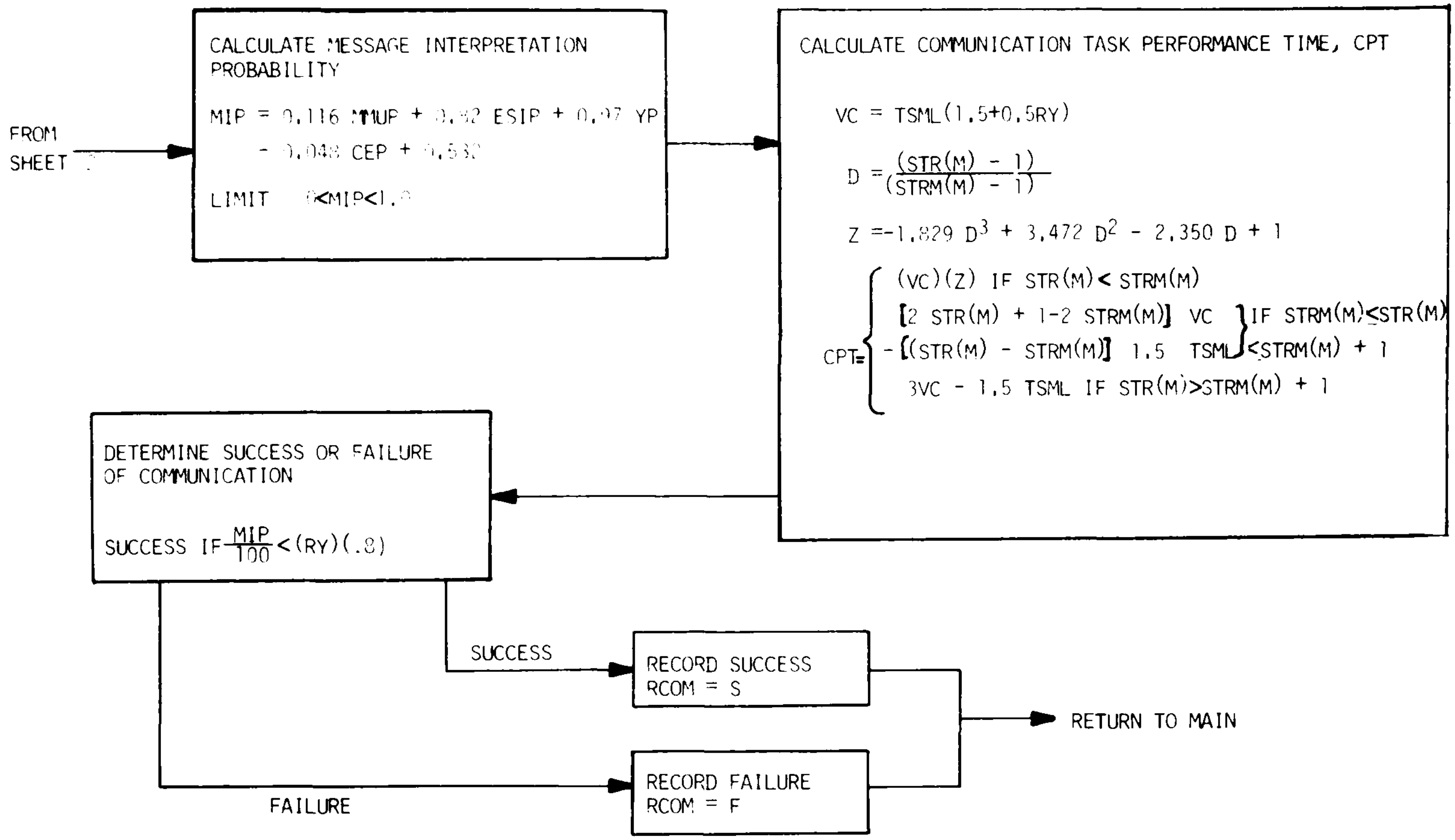


FIGURE 7-2. COMMUNICATIONS SUBROUTINE DETAIL LOGIC (CONTINUED)

TABLE 7-1

PARAMETERS AND INPUT FOR COMMUNICATION MODULE

	Parameter or Input Data Item	*Data Name*
1.	Operator number who receives the communication	M
2.	Message Length Code S - short (mean length 50 words) M - medium (mean length 100 words) L - long (mean length 200 words)	MSGLC
3.	Mean sentence length (words per sentence) over all communication tasks. Default value MSL = 18.6 words.	MSL
4.	Standard deviation of sentence length (words per sentence) over all communications tasks. Optional, default: SSL = 8.1 words.	SSL
5.	Current stress value of receiving operator STR(M)$\geqq$1	STR(M)
6.	Stress threshold value for operator M, the value of stress at which performance begins to change for the worse.	STRM(M)

TABLE 7-2

DATA ITEMS USED IN THE COMMUNICATIONS MODULE

Item	*Data Name*
Sentence number in message	SE
Number of last sentence in message	SEMAX
Length of sentence (number of words)	SLEN(SE)
Random deviate, pseudo random number from a normal distribution mean = 0, sigma = 1)	RD
Pseudo random number equiprobable in the interval 0 to 1	RY
Length of the message (number of words)	MSGLN
Temporary storage for message length	TMSGLN
Total length of all sentences in the message (words)	TSLN
Average sentence length over this particular message	ASL
Yngve depth of message	YD
Yngve depth percentile	YP
Center embeddedness of each sentence (1 or 0)	CE(SE)
Total center embeddedness tally	TCE
Center embeddedness of message	CEMSG
Center embeddedness percentile$\leqq$90	CEP
Number of different nouns in the message	NDN
Final value of NDN	FNDN
Memory for semantic units over entire message	MMU
MMU percentile	MMUP
Number of abbreviations per hundred words	RA
Evaluation of symbolic implications	ESI
Number of abbreviations per message	NA
ESI percentile	ESIP
Message Interpretation probability	MIP
Communication task performance time	CPT
Average value of communications time without stress factors	VC
A stress-to-threshold ratio used in CPT calculation	D

TABLE 7-3

COMMUNICATION SUBROUTINE OUTPUTS

Output	*Data Name*
Communication Performance Time (Secs)	CPT
Results of communications	RCOM
S - successful U - unsuccessful	

MESSAGE LENGTH

Message length is based on an input value by message. The mean value is determined by the model user. Three input message length levels are permitted: (1) short—mean length = 50 words, standard deviation = 15, (2) medium—mean length = 100 words, standard deviation = 30, and (3) long—mean length = 200 words, standard deviation = 45.

SENTENCE LENGTH

The mean and standard deviation were computed of the length of the sentences which Williams et al. used in developing the norms describing Air Force technical literature. These values were 18.6 and 8.1, respectively. The model user may assign a mean and standard deviation of sentence length within messages. If such an assignment is not made, the default values above are employed. Sentences lengths are generated until the total of their lengths equals or exceeds the previously determined message length.

YD CALCULATION

Two hundred sentences were selected from the samples of Air Force materials on which the previously described norms were based. The selection of these sentences was systematic and unbiased. A regression equation was calculated which related YD to sentence length:

$$\text{YD} = .028\ (\text{average sentence length}) + 1.146.$$

The correlation between the two variables is .60.

The data required for the accuracy of interpretation equation are a percentile value. To obtain the required percentile value, we determine the mean YD of the sentences of the message or message block. We then determine the percentile value through reference to the following normative table:

Mean YD	*Percentile Value*
$1.97 < x$	5 (least interpretable)
$1.86 < x \leq 1.97$	15
$1.79 < x \leq 1.86$	25
$1.75 < x \leq 1.79$	35
$1.69 < x \leq 1.75$	45
$1.64 < x \leq 1.69$	55
$1.60 < x < 1.64$	65
$1.57 < x \leq 1.60$	75
$1.48 < x \leq 1.57$	85
$x \leq 1.48$	95 (most interpretable)
or, simplifying:	Percentile = 389 — YD/.005.

CE CALCULATION

CE is also related to sentence length. However, CE is handled in the simulation in a somewhat different manner. As in the case of YD, an equation relating CE to sentence length was developed for the 200 sentences systematically selected from the set of Air Force messages on which the previously described norms were based. In this case, the resulting equation was:

$$CE = .0206\,(\text{sentence length}) + .003$$

and the correlation between the two variables was over .90. Since fractional values of CE are meaningless, the value computed for CE is taken as a probability of center embedded material appearing in the applicable sentence. The computed probability is compared to a randomly selected value between 0.0 and 1.0. If the probability value exceeds the randomly selected value, then the sentence contains center embedded material. The CE level of a total message is computed as the number of sentences of the message which are determined to contain center embedded material divided by the number of sentences in the message. This value is converted to the required percentile value for input to the multiple regression equation through reference to tabulated values. The values for determining CE percentiles are:

CE Value	*Percentile*
$x > .877$	5 (least interpretable)
$.877 \geq x > .773$	15
$.773 \geq x > .566$	25
$.566 \geq x > .416$	35
$.416 \geq x > .307$	45
$.307 \geq x > .184$	55
$.184 \geq x > .100$	65
$.100 \geq x > .038$	75
$.038 \geq x > 0.00$	85
$x = 0.00$	90 (most interpretable)

Twenty percent of the Air Force Messages studied had no center embedding. Hence, the percentile corresponding to a CE value of 0.00 is 90, the midpoint of a set of samples lacking any center embedded material.

MMU CALCULATION

The variable MMU is a measure of the number of different nouns present in a message. Such a measure should be affected by message length. In a brief message, each word used might appear a single time. As the message grows longer, more and more words will be used which have appeared previously, and words novel to the message should be encountered with increasing rarity. Chotlos (1944) found the number of different words appearing in a language sample to vary as a function of message length. Chotlos presented equations describing the vocabulary diversity of students of below average, average, and above average tested I.Q. The equation for above average students seems most applicable to the AN UPD-X situation. For this subject group:

$$D = \frac{N}{9.551}\,(10.321 - \log_e N)$$

in which D represents the number of different words appearing in a message and N represents the length of the message.

According to the above equation, a 100 word message should contain 59.8 different words. Williams et al. (1977), found a mean of 61.8 different words in their 100 word message blocks. Chotlos' equation fits these data very closely.

Williams et al. found a mean of 19.8 different nouns per 100 word message in the same work. This value is very nearly one third of the mean number of different words of all types found in those samples. Hence, number of different nouns, (NDN) is determined by dividing the value obtained through Chotlos' formula above by three, or

$$NDN = \frac{N}{9.551}\,(10.321 - \log_e N)/3.$$

The NDN value to be used in computing MMU is randomly selected from a normal distribution whose mean equals the value of NDN and whose standard deviation equals one third of the value of NDN. This final value of NDN is used, with message length, ML, to determine the MMU value of the message, according to the formula

$$\text{MMU} = 1 - \frac{\text{NDN}}{\text{ML}}$$

The percentile value corresponding to the obtained MMU level is obtained by reference to the following tabulated values:

MMU Value	*Percentile*
$x < .783$	5 (least interpretable)
$.783 \leq x < .802$	15
$.802 \leq x < .813$	25
$.813 \leq x < .824$	35
$.824 \leq x < .832$	45
$.832 \leq x < .841$	55
$.841 \leq x < .850$	65
$.850 \leq x < .861$	75
$.861 \leq x < .874$	85
$.874 \leq x <$	95 (most interpretable)

ESI CALCULATION

ESI is calculated as the number of abbreviations present in a message divided by the length of the message, and that quotient subtracted from unity. In the work of Williams et al. (1976), 1.47 abbreviations were found per 100 words, on the average. The standard deviation of rate of occurrence was found to be 1.95. The rate of occurrence of abbreviations in each simulated message is determined by randomly selecting a value from a normal distribution whose mean is 1.47 and whose standard deviation is 1.95. This rate of occurrence of abbreviations per 100 words is multiplied by message length/100 to determine the number of abbreviations in the message. The obtained value is rounded to the nearest integer, and the ESI value is then computed according to the following relationship:

$$\text{ESI} = 1 - \frac{\text{NA}}{\text{ML}},$$

in which number of abbreviations is represented by NA and message length is represented by ML.

The obtained ESI value is, again, transformed to a percentile via tabulated values:

ESI Value	*Percentile*
$x < .943$	5 (least interpretable)
$.943 \leq x < .967$	15
$.967 < x < .979$	25
$.979 \leq x < .989$	35
$.989 \leq x < .992$	45
$.992 < x < .998$	55
$.998 \leq x < 1.00$	65
$x \quad 1.00$	80 (most interpretable)

Thirty percent of the Air Force messages studied had no abbreviations. Hence, the percentile value corresponding to an ESI value of 1.00 is 80, the midpoint of the set of samples lacking any abbreviations.

MESSAGE INTERPRETATION PROBABILITY

Message interpretation probability is based on the CE, YD, MMU, and ESI percentile values derived in earlier steps. The derived percentiles are entered into Equation 3 and a probability value is determined. The probability value is compared with a random number to determine interpretation success or failure. In the case of success, the results are stored for access by the main routine. In the case of failure, the next task to be simulated is determined by MAIN.

MESSAGE TIME

Miller (1951) stated that the average rate of speech is approximately 1.5 words per second. This value, with a standard deviation of 0.5, is employed to determine communication time in the AN UPD-X simulation as a function of message length in words.

STRESS

As discussed elsewhere in the present report, the value of stress is available for each operator in the AN UPD-X system simulation. With regard to communication, stress is allowed to influence the rate of speech, hence message time. Stress is allowed to cause speech rate to increase until the spearker's stress threshold is attained. At stress levels above the speaker's stress threshold, speech rate falls to the speaker's base rate. Stress does not affect accuracy of message interpretation in the AN UPD-X simulation.

PROGRAMMATIC ASPECTS

In this section those human-effects which have been described are converted into a form suitable for definition of a computer subroutine, termed the communications subroutine or communications module. This subroutine is entered by the main program once for every communication task of the mission. It simulates the receipt of a single message containing a number of sentences designated by SEMAX by a single receiver whose operator number is designated by M. The principal results of the communication module are:

(1) an indicator as to whether or not the communication was successful (RCOM = S or U).

(2) the length of time, in seconds, required for the communication, i.e., the communication performance time (CPT).

INPUTS

The data items shown in Table 7-1 are those which are provided as inputs to be made available from the main program to the communication subroutine. If there is more than one message receiver, the analyst selects the operator (M) whose receipt of the message is most important. The message length code specifies the class in which the size of the message to be transmitted falls. This applies only to the single message, i.e., the specific task being simulated. Note that the mean sentence length, MSL, and its standard deviation, SSL, (both of which inputs are optional) are values which are applicable over all communication tasks in the mission. To cause the use of the default values (MSL = 18.6, SSL = 8.1) set the input for MSL = 0. The current value of stress and stress threshold applicable to the receiving operator are as defined in other modules in this series.

LOGIC FOR COMMUNICATIONS SUBROUTINE

Figure 7-2 shows the detailed logic for the communication module and as such corresponds to the general logic flow chart shown in Figure 7-1. For each data processing element shown within a box in Figure 7-1, there are one or more similar boxes in Figure 7-2. These detail the operations to be performed, together with data item processing descriptions to accomplish the required processing. Thus Figure 7-2 is suitable for use as a specification for the preparation of the communications module computer program.

Each of the data items used in Figure 7-2 is defined and explained in Table 7-2.

During these calculations, pseudo random numbers RD and RY are calculated using routines assumed to be available in the library for the selected computer. Note that a different value should be calculated for each use/encouter of either of these pseudo random numbers.

The number of words in the message, MSGLN, is calculated in the first block of Figure 7-1, and is used to determine the average length of the sentences comprising the message (3rd box). Note, in box 3, that in order to have an integral number of sentences represented in the average, that the total of all words in all sentences of the message (TSLN) will usually exceed the original number of words in the sentence MSGLN. Therefore, the TSLN value is used thereafter as the actual message length (e.g., in the MMU calculation). Each entry of the subroutine will therefore begin with the generation of a new message whose size is selected by a Monte Carlo approach.

The values of Yngve depth (YD), center embeddedness (CE), Memory for Semantic Units (MMU), and Evaluation of Symbolic Implication (ESI) are determined and for each of these a percentile value is then determined as described above.

The probability of correct message interpretation, MIP, is determined by Equation 3 followed by the stress STR(M) and performance time (CPT) determination. The CPT equations are essentially those same stochastic relationships utilized in the scan detect module with adaption to the basic element of communication time, the number of seconds per word.

Success or failure is determined and recorded last by comparing a pseudo random number in the 0 to 0.8 range with MIP 100.

SECTION VIII
CONCLUSIONS

Generality was a goal in the algorithm designs so that the resulting simulation modules will be valid across various equipment configurations and system designs for the AN/UPD-X. This objective of the modules was achieved in that a user of any module need only modify input parameters in order to accommodate system oriented feature differences, such as:

- radar coverage
- display characteristics
- target types
- display size
- target resolution
- operator ability
- mission time
- communications load
- decision aiding features
- operator training requirements
- operator load imposed

The end products are considered to enhance a total AN/UPD-X man-machine model.

The modules are rich in variables relevant to the particular AN/UPD-X system application, yet are designed so as not to overpower the MAIN simulation program itself in complexity, computer memory, or computer run time required. As can be seen above, the variables are relevant to many other applications where the systems or subsystems are similar. Modularity allows each module to be independently utilized or any combinations formed to simulate a host of system types and configurations.

REFERENCES FOR THE SCAN/DETECT MODULE

Baker, C.H., & Earl, W.K. *Visual detection of positive versus negative pips on a radar PPI.* (Technical Memorandum 750-1). Goleth, CA: Human Factors Research, February, 1968.

Blackwood, H.R. Contrast thresholds of the human eye. *Journal of the Optical Society of America,* 1946, *36.*

Brainard, R.W., & Caum, K.B. *Evaluation of an image quality enhancement technique.* (AMRL-TR-65-143). Wright-Patterson Air Force Base OH: Aerospace Medical Research Laboratory, September, 1965. AD 624 470.

Brown, J.L., & Mueller, C.G. Brightness discrimination and brightness contrast. In C.H. Graham (Ed.), *Vision and visual perception.* New York: Wiley, 1965.

Chapanis, A. How we see: A summary of basic principals. In Panel on Psychology and Physiology (Eds.). *A survey report on human factors in undersea warfare.* Washington: National Research Council, 1949.

Greening, C.P. Mathematical modeling of air-to-ground target acquisition. *Human Factors,* 1976, *18,* 111-148.

Harrisman, M.W. & Williams, S.B. Visibility on cathode ray tube screens: Positive vs. negative signals on an intensity modulated scope. *Journal of the Optical Society of America,* 1950, *40,* 102-104.

Heinz, M. & Lippay, F. Ueber die Beziehungen zeischen der Unterschiedsempfidlichkeit unb der Zanl der eraegten Sinneselemente: I. *Pflug. Arch. Ges. Physiol.,* 1928, *218,* 437-447. (C.H. Graham (Ed.). *Vision and vision perception.* New York: Wiley, 1965.)

Kinzly, R.E., & Akerman. *Visual detection for optical countermeasures.* (AFAL-TR-76) Air Force Avionics Laboratory. 1976 (Ward, F.E. *Ground to air target detection: A review of variables and models.* Fairborn, OH: Wright State University, August, 1977.)

Lamar, E., Hecht, S., Shlaer, & Hendley, C.D. Size, Shape, and Contrast in Detection of Targets by Daylight Vision. I. *Journal of the Optical Society of America,* 1947, **37,** 531-545.

Ozkaptan, H., Onmart, J.G. Bengeat, J.W., & McGee, R.A. *Target acquisition studies: Fixed television fields of view.* (OR 9656) Orlando, FLA: Martin Marietta Corp., October, 1968.

Pieron, H. De la summation spatiale des impressions lumineuses au niveau de la fovea. Anna Psychologica, *30,* 87-105. (Woodworth, R.S., & Schosberg, H. *Experimental Psychology.* (Revised Ed.) New York: Holt, March, 1955.

Taylor, J.H. *Contrast thresholds as a function of retinal position and target size for the light adapted eye.* (S O Reference 61-10) University of California Visibility Laboratory, 1961.

Taylor, J.H. Contrast thresholds as a function of retinal position and target size for the light-adapted eye. In M.A. Whitcomb (Ed.), *Visual Problems of the Armed Forces.* Washington: National Academy of Sciences. 1962. (NTIS No. AD 272-762).

Ward, F.E. *Ground to air target detection: A review of variables and models.* Fairborn, OH: Wright State University, August, 1977.

Williams, L.G., Fairchild, D.D., Graf, C.P., Juola, J.F., & Trumm, G.A. *Visual search effectiveness for night vision devices.* St. Paul, MN: Honeywell, Inc. May, 1970. (NTIS No. AD B 008 760).

Woodworth, R.S., & Schlosberg. *Experimental Psychology* (Revised Ed.) New York: Holt, March, 1955.

REFERENCES FOR THE CLASSIFICATION MODULE

Aiken, L.S. & Brown, D.R. A feature utilization analysis of the perception of pattern class structure. *Perception and Psychophysics*, 1971, *9*, 279-283.

Arnoult, M.D. Prediction of perceptual responses from structured characteristics of the stimulus. Perceptual and Motor Skills, 1960, *11*, 261-268.

Brainard, R.W., & Caum, K.B. *Evaluation of an image quality enhancement technique.* (AMRL-TR-65-143). Wright-Patterson AFB, Ohio: Aerospace Medical Research Laboratoy, October, 1964. AD 624 470.

Brainard, R.W., & Ornstein, G.N. *Image quality enhancement.* (AMRL-TR-65-28). Wright-Patterson AFB, Ohio: Aerospace Medical Research Laboratory, April, 1965. AD 616 895.

Brown, B.R. & Aylworth, C.E. Feature encoding and classification with sequentially presented Markov stimuli. *Perception and Psychophysics,* 1970, *9*, 203-207.

Brown, D.R. & Michels, K.M. Quantification procedures, stimulus domains, and discrimination difficulty. *Perceptual and motor Skills*, 1960, *22*, 421-422.

Bruns, R.A., Bittner, A.C., & Stevenson, R.C. *Effects of target size, target contrast, viewing distance on dynamic televisual target detection and identification.* (TP-72-24. Technical Publication). Point Magu: Naval Missile Center, 1972.

Caldwell, E.C. & Hall, V.C. Distinctive features versus prototype learning reexamined. *Journal of Experimental Psychology*, 1970, *83*, 7-12.

Cheokosky, S.F. Speeded classification of multidimensional stimuli. *Journal of Experimental Psychology*, 1971, *87*, 383-388.

Coluccio, T. & Wasielewski, J. Electro-optical image enhancement. (RADC-TR-70-35). Rome, N.Y.: Grifiss Air Force Base, 1970.

Dick, A.O. Processing time for naming and categorization of letters and numbers. Perception and Psychophysics, 1971, *9*, 350-352.

Dumas, J. & Gross, E. Effects of attribute probability on response criterion adjustments in a memory retrieval task. *Journal of Experimental Psychology*, 1973, *101*, 307-313.

Dumas, J., Gross, E., & Checkosky, S.F. The effects of attribute probability in a memory search task. *Journal of Experimental Psychology*, 1972, *93*, 327-332.

Fitts, P.M., Weinstein, M., Rappaport, M., Anderson, N. & Leonard, J.A. Stimulus correlates of visual pattern recognition: A probability approach. *Journal of Experimental Psychology*, 1956, *51*, 1-11.

Gyr, J.W., Brown, J.S., Willey, R., & Zivan, A. Computer simulation and psychological theories of perception. *Psychological Bulletin*, 1966, *65*, 174-192.

Hake, H.H. Form discrimination and the invariance of form. In L. Uhr (Ed.). *Pattern recognition*. New York: Wiley, 1966.

Jensen, H. Side-looking airborne radar. *Scientific American*, 1977, *237*, 84-95.

Kirsner, K. An analysis of the visual component in recognition memory for verbal stimuli. *Memory and Cognition*, 1973, *1*, 449-453.

Levine, J.M. & Eldredge, D. *Effects of ancillary information upon photointerpreter performance.* Arlington: Army Research Institute for the Behavioral and Social Science, 1974.

MacLeod, S. *Photointerpreter performance studies.* RADC-TDR-64-326). Rome: Grifiss Air Force Base, 1964.

Martin, F.F. *Computer modeling and simulation.* New York: John Wiley & Sons, 1968.

Miller, G.M., Heise, G.A., & Lichten, W. The intelligibility of speech as a function of the context of test materials. *Journal of Experimental Psychology,* 1951, *41,* 329-345.

Nickerson, R.S. Categorization time with categories defined by disjunctions and conjunctions of stimulus attributes. *Journal of Experimental Psychology,* 1967, 73, *211-219.*

Nickerson, R.S. & Feehrer, C.E. Stimulus categorization and response time. *Perceptual & Motor Skills,* 1964, *18,* 785-793.

Pick, A.D. Improvement of visual and tactual form discrimination. *Journal of Experimental Psychology,* 1965, *69,* 331-339.

Posner, M.I. & Keele, S.W. Retention of abstract ideas. *Journal of Experimental Psychology,* 1970, *83,* 304-308.

Reder, L.M., Anderson, J.R., & Bjork, R.A. A semantic interpretation of encoding specificity. *Journal of Experimental Psychology,* 1974, *102,* 648-656.

Reed, S.K. *Psychological processes in pattern recognition.* New York: Academic Press, 1973.

Rusis, G. & Snyder, H.L. The effects of TV camera field of view and size of targets upon air-to-ground target recognition. *Human Factors,* 1965, *7,* 493-501.

Siegel, A.I. & Wolf, J.J. *Man machine simulation models.* New York: Wiley, 1969.

Steedman, W.C. & Baker, C.A. Target size and visual recognition. *Human Factors,* 1960, *2,* 120-127.

Sternberg, S. Memory scanning: mental processes revealed by reaction time experiments. *American Scientist,* 1969, *57,* 421-457.

Naylor, T.H., Balinsfy, J.L., Burdick, D.S. & Chu, K. *Computer simulation techniques.* New York: Wiley, 1966.

Thomson, D.M. & Tulvig, E. Associative encoding and retrieval: Weak and strong cues. *Journal of Experimental Psychology,* 1970, *86,* 255-262.

Tou, J.T. Feature selection for pattern recognition systems. In S. Wanatabe (Ed.) *Methodologies of pattern recognition.* New York: Academic Press, 1969.

Tulvig, E. & Thomson, D.M. Encoding specificity and retrieval processes in spisodic memory. *Psychological Review,* 1973, *80,* 352-373.

Uhr, C. "Pattern recognition" computers as models for form perception. *Psychological Bulletin,* 1963, *60,* 40-73.

Uhr, L. (Ed.) *Pattern recognition: Theory, experiments, computer simulation, and dynamic models of form perception and discovery.* New York: Wiley, 1966.

Wanatabe, S. (Ed.) *Methodologies of pattern recognition.* New York: Academic Press, 1969.

Zusne, L. *Visual perception of form.* New York: Academic Press, 1970.

REFERENCES FOR THE ALTERNATE CLASSIFICATION MODULE

Aiken, E.G. Auditory discrimination learning: Prototype storage and distinctive feature detection mechanisms. *Perception and Psychophysics,* 1969, *6,* 95-96.

Anderson, N.H. Integration theory and attitude change. *Psychological Review,* 1971, *78,* 171-206.

Franks, J.J., & Bransford, J.D. Abstraction of visual patterns. *Journal of Experimental Psychology,* 1971, *90,* 65-74.

Gibson, J.J. *The senses considered as perceptual systems.* Boston: Houghton-Mifflin, 1966.

Gibson, J.J., & Gibson, E. Perceptual learning: Differentiation or enrichment? *Psychological Review,* 1955, *63,* 32-41.

Luce, R.D. Detection and recognition. In R.D. Luce, R.R. Bush, & E. Galenter (Eds.), *Handbook of Mathematical Psychology,* (Volume I). New York: Wiley, 1963.

Pick, A. Improvement of visual and tactual form discrimination. *Journal of Experimental Psychology,* 1965, *69,* 331-339.

Rodwan, A.S., & Hake, H.W. The discriminant function as a model for perception. *American Journal of Psychology,* 1964, *77,* 380-392.

Rosh, E.H. On the internal structure of perceptual and semantic categories. In T.M. Moore (Ed.), *Cognitive development and the acquisition of language.* New York: Academic Press, 1973.

Sperling, G. Successive approximations to a model for short-term memory. *Acta Psychologica,* 1967, *27,* 285-292.

Sternberg, S. Two operations in character recognition: Some evidence from reaction time measurements. *Perception and Psychophysics,* 1967, *2,* 45-53.

Townsend, J.T. Theoretical analysis of an alphabetic confusion matrix. *Perception and Psychophysics,* 1971, *9,* 40-50.

REFERENCES FOR THE DECISION MODULE

Coombs, C.H. On the use of inconsistency of preferences in psychological measurement. *Journal of Experimental Psychology,* 1958, *55,* 1-7.

Cornballis, M.C., & Miller, A. Scanning and decision processes in recognition memory. *Journal of Experimental Psychology,* 1973, *98,* 379-386.

Edwards, W. The theory of decision making. *Psychological Bulletin,* 954, *51,* 380-417.

Edwards, W. Behavioral decision theory. *Annual Review of Psychology,* 1961, *12,* 473-498.

Fischler, I., & Juola, J.F. Effects of repeated tests on recognition time for information in long-term memory. *Journal of Experimental Psychology,* 1971, *91,* 54-58.

Fishburn, P. *Decision and value theory*. New York. Wiley, 1964.

Howard, D.V. Search and decision processes in intentional forgetting. *Journal of Experimental Psychology: Human Learning and Memory*, 1976, *2*, 566-576.

Juola, J.F., Taylor, G.A., & Young, M.E. Stimulus encoding and decision process in recognition memory. *Journal of Experimental Psychology*, 1974, *102*, 1108-1115.

Keele, S.W. Effects of input and output modes on decision time. *Journal of Experimental Psychology*, 1970, *85*, 157-162.

Kennedy, A. Decision latencies to thematic and nonthematic distractions in prose. *Journal of Experimental Psychology*, 1973, *98*, 432-434.

Koppell, S. Decision latencies in recognition memory: A signal detection theory analysis. *Journal of Experimental Psychology: Human Learning and Memory*, 1977, *3*, 445-447.

Laming, D.R.J. *Information theory of choice-reaction times*. New York: Academic Press, 1968.

Lovelace, E.A., & Snodgrass, R.D. Decision times for alphabetic order of letter pairs. *Journal of Experimental Psychology*, 1971, *88*, 258-264.

Luce, R.D. *Individual choice behavior*. New York: Wiley, 1959.

Newell, A., & Simon, H.A. *Human problem solving*. Englewood Cliffs, N.J.: Prentice-Hall, 1972.

Otzada, R. Decision latencies in short-term recognition memory. *Journal of Experimental Psychology*, 1971, *90*, 27-32.

Paterson, T.T. *Job evaluation: A new method* (Vol. 1). London, England: Business Books Limited, 1972.

Pitz, G.F., & Geller, E.S. Revision of opinion and decision times in an information-seeking. *Journal of Experimental Psychology*, 1970, *83*, 400-405.

Seibel, R. Discrimination reaction time for a 1,023-alternative task. *Journal of Experimental Psychology*, 1963, *66*, 215-219.

Siegel, A.I., & Wolf, J.J. *Man-machine simulation models: Psychological and performance interaction*. New York: Wiley, 1969.

Siegel, A.I., Wolf, J.J., Fischl, M.A., Miehle, W., & Chubb, G.P. *Modification of the Siegel-Wolf operator simulation model for on-line experimentation* (AMRL-TR-71-60). Wright-Patterson Air Force Base, Ohio: Aerospace Medical Research Laboratory, June, 1971. AD 737798.

Simon, H.A., & Newell, A. Human problem solving: The state of the theory in 1970. *American Psychologist*, 1971, *26*, 145-159.

Thurstone, L.L. A law of comparative judgment. *Psychological Review*, 1927, *34*, 273-286.

REFERENCES FOR THE COMMUNICATION MODULE

Bormuth, J.R. Comparable cloze and multiple-choice comprehension test scores. *Journal of Reading*, 1967, *10*, 291-299.

Bormuth, J.R. Cloze test readability: criterion referenced scores. *Journal of Education Measurement*, 1968, *5*, 189-196.

Bormuth, J.R. *Development of readability*. (Final Report, Project No. 7-0052). Washington, D.C.: U.S. Department of Health, Education and Welfare, 1969.

Chotlos, J.W. A statistical and comparative analysis of individual written language samples. In J.F. Dashiell (Ed.), Studies of language behavior. *Psychoiogical Monographs*. 1944, *56*, (2, Whole No. 255).

Guilford, J.P. *The nature of human intelligence*. New York: McGraw-Hill, 1967.

Guilford, J.P., Comrey, A.L., Green, R.F., & Christensen, P.R. *A factor analytic study of reasoning abilities. I. Hypotheses and description of tests*. Los Angeles: University of Southern California, 1950.

Guilford, J.P., Geiger, R.N., & Christensen, P.R. *A factor analytic study of planning. I. Hypotheses and description of tests*. Los Angeles: University of Southern California, 1954.

Guilford, J.P., & Hoepfner, R. *Structure-of-intellect factors and their tests*. Los Angeles: University of Southern California, 1966.

Hoepfner, R., Guilford, J.P., & Merrifield, P.R. *A factor analysis of the symbolic-evaluation abilities*. Los Angeles: University of Southern California, 1964.

Lambert, J.V., & Siegel, A.I. Psycholinguistic determinants of readability. In A.I. Siegel and J.R. Burkett (Eds), *Applications of the structure-of-intellect and psycholinguistic concepts to reading comprehensibility measurement*. (AFHRL-TR-74-49). Lowry AFB, Colo.: Air Force Human Resources Laboratory, September 1974.

Miller, G.A. Speech and language. In S.S. Stevens (Ed.), *Handbook of experimental psychology*. New York: John Wiley & Sons, 1951.

Rankin, E.F., & Culhane, J.W. Comparable cloze and multiple choice comprehension test scores. *Journal of Reading*, 1963, *13*, 193-198.

Schwartz, D., Sparkman, J.P., & Deese, J. The process of understanding and judgements of comprehensibility. *Journal of verbal learning and verbal behavior*. 1970, *9*, 87-93.

Siegel, A.O., & Bergman, B.A. Readability comprehensibility as related to the structure-of-intellect model. In A.I. Siegel & J.R. Burkett (Eds.), *Application of the structure-of-intellect and psycholinguistic concepts to reading comprehensibility measurement*. (AFHRL-TR-74-49) Lowry AFB, Colo.: Air Force Human Resources Laboratory, September 1974.

Siegel, A.I., Williams, A.R., Lapinsky, W.T., Warms, T.A., Wolf, J.J., Groff, S.D., & Burkett, J.R. *Studies and design specifications for computurized measurement of textual comprehensibility*. (AFWRL-TR-76-77) Lowry AFB, Colo.: Air Force Human Resource Laboratory, October, 1976.

Williams, A.R., Siegel, A.I., Burkett, J.R., & Groff, S.D. *Development and validation of an equation for predicting the comprehensibility of textual material*. (AFHRL-TR-77-8) Lowry AFB, Colo.: Air Force Human Resources Laboratory, February 1977(a).

Yngve, V.H. A model and an hypothesis for language structure. *Proceedings of the American Philosophical Society*, 1960, *104*, 444-466.

REFERENCE NOTE

Williams, A.R., Siegel, A.I., Burkett, J.R., & Groff, S.D. Unpublished data. The equation presented was derived as part of the work of Williams et al. (1977(a) but was not presented in their report, 1977(b).

REFERENCES

Analytics. 1975. *Introduction and Overview*. The Human Operator Simulator. Vo. 1. Technical Report 1117-I. Willow Grove, Pennsylvania.

Analytics. 1975. *HOS Users' Guide*. The Human Operator Simulator. Vol. 2. Technical Report 1181-A. Willow Grove, Pennsylvania.

Analytics. 1976. *HAL Programmers Guide*. The Human Operator Simulator. Vol. 3. Technical Report 1181-C. Willow Grove, Pennsylvania.

Analytics. 1974. *HOS Programmers Guide*. The Human Operator Simulator. Vol. 4. Technical Report 1117-B. Willow Grove, Pennsylvania.

Analytics. 1974. *HODAC Programmers Guide*. The Human Operator Simulator. Vol. 5. Technical Report 1117-A. Willow Grove, Pennsylvania.

Analytics. 1975. *HOS Simulation Descriptions*. The Human Operator Simulator. Vol. 6. Technical Report 1181-B. Willow Grove, Pennsylvania.

Analytics. 1976. *LAMPS Air Tactical Officer Simulation*. The Human Operator Simulator. Vo. 7. Technical Report 1200. Willow Grove, Pennsylvania.

Analytics. 1977. *Applications to Assessment of Operator Loading*. The Human Operator Simulator. Vol. 8. Technical Report 1233-A. Willow Grove, Pennsylvania.

Analytics. 1978. *P-3C SS-3 Operator Station Cost Effectiveness Evaluation*. The Human Operator Simulator. Vol. 10. Technical Report 1289. Willow Grove, Pennsylvania.

Duket, S.D., Wortman, D.B., Seifert, D.J., Hann, R.L., Chubb, G.P. (1977). *Documentation for the SAINT Simulation Program*. Aerospace Medical Research Laboratory, Wright-Patterson Air Force Base, Ohio, AMRL-TR-77-63. AD A059 198.

Wortman, D.B., Duket, S.D., Seifert, D.J., Hann, R.L., Chubb, G.P. (1977a). *Simulation Using SAINT: A User-Oriented Instruction Manual*. Aerospace Medical Research Laboratory, Wright-Patterson Air Force Base, Ohio, AMRL-TR-77-61. AD A058 671.

Wortman, D.B., Duket, S.D., Seifert, D.J., Hann, R.L., Chubb, G.P. (1977b). *The SAINT User's Manual*. Aerospace Medical Research Laboratory, Wright-Patterson Air Force Base, Ohio, AMRL-TR-77-62. AD A058 724

Wortman, D.B., Duket, S.D., Seifert, D.J., Hann, R.L., Chubb, G.P. (1977c). *An Example to Illustrate the Use of SPSS for the Analysis of a SAINT Model*. Aerospace Medical Research Laboratory Wright-Patterson Air Force Base, Ohio, AMRL-TR-77-64. AD A058 723.

☆U.S.Government Printing Office: 1981 — 757-002/393

DA

FIL

5 –